ASSESSMENT OF TOOL CONDITIONING AND MONITORING DURING GRINDING PROCESS: A REVIEW

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Article History: Received: 12 July 2018 Revised: 14 August 2018 Accepted: 15 September 2018

Abstract

The state of the grinding wheel during the grinding process must be closely monitored because it has a direct impact on the workpiece's surface precision. The fluctuation in the machine sound during the grinding process is critical for the field operator to determine whether the grinding wheel is worn or not. The tool condition utilized in the machining process is typically defined by its wear state, which is a significant element in determining the manufacturing processes' machining efficiency. The purpose of this review is to provide a method for estimating the tool condition of a grinding wheel by studying different techniques such as an image sensor, machine learning algorithms, Decision Tree, and Acoustic Emission sensing. The simplified wear model's statistical characteristics, mean, standard deviation, and entropy were compared. Finally, machine learning methods and other techniques were utilized to combine statistical information to predict the grinding wheel's wear status. The results indicate that the Acoustic emission using machine learning could predict the tool wear with a high accuracy of 99%. Additionally, the field operator might evaluate the grinding wheel's wealth by changing the grinding sound or adding noise filters.

Keywords: Conditioning; Monitoring; Grinding; Machine Learning; Acoustic Emission.

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DOI:10.17628/ecb.2018.7.357-366

1. Introduction

Reducing process durations and more flexibility are becoming increasingly important in the manufacturing sector as the need for higher precision and material durability rises. To satisfy the growing need for functional efficiency at a reasonable budget, traditional techniques such as preventative maintenance and reactive "fail-and-fix" procedures are not sufficient. Furthermore, ensuring a high standard of production continues to be a difficult task since manufacturing techniques are susceptible to constant change Akbar et al., 2010). It is hoped that the use of “Intelligent Manufacturing Systems” (IMS) would convert maintenance into predictive dependability, allowing for a constant standard of excellence to be retained during the production cycle (Klocke et al., 2018).

Grinding is a material removal technique that is used to manufacture workpiece material to certain parameters and surface accuracy. One of the most critical steps in the manufacturing process is the grinding process, which is used to generate extreme dimensional quality, accuracy, precision, and finishing (Lezanski 2001; Tönshoff et al., 2002). Thus, it becomes very critical to monitor the grinding tool, i.e., the grinding wheel as the grinding process consists of the majority portion of the total manufacturing process.

Traditionally, the choice of the maintenance frequency for grinding tool wear is usually made by a competent worker on an approximate scale. But generally, it has been seen that the grinding wheel/tool gets worn out before the dressing process due to the unavailability of precise data and techniques to pre-identify the grinding tool worn out point. This leads to the degradation of the quality of the finished product. On the other hand, if the dressing of the grinding wheel is carried out before the wheel worn out point, the grinding efficiency of the process would also decrease. So, it is essential to predetermine the tool's worn-out point during the grinding process so that the manufacturing process efficiency does not get affected. Fig 1 shows the process of grinding wheel wear mechanism (Oliveira et al., 2009).

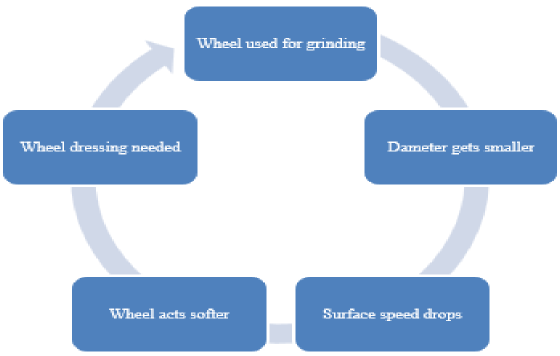

Figure 1 Grinding Wheel wear Mechanism.

Tool wheel wear is a common thing in the manufacturing operations of grinding wheels. Surface roughness rises when materials are ground with aggressive media. These factors combine to make abrasive grinding dangerous for humans as well as machine parts. Furthermore, abrasive wear is a very complicated, nonlinear process that is influenced by a variety of variables and techniques (Xiang et al., 2018; Novoselov et al., 2016). Due to the rough grinding layer, very tiny degradation of the grinding wheel, unavailability of adequate time for detection, and difficulties in evaluation in the ongoing process, high-accuracy measurement of grinding wheel wear is difficult to accomplish (Wegener et al., 2017; Ahrens et al., 2017).

The dressing is the procedure of removing worn-out particles from the grinding wheel utilizing a diamond indenter with single or multiple points. Dressing the grinding wheel is critical for maintaining cutting capabilities and ensuring that the grinding wheel rotates properly to the machine's shaft centre (Ding et al., 2014). The frequency of dressing is essential to extracting worn-out elements and is critical for removing fine granules and ruptured tiny particles. A critical stage in the dressing process is to establish a parameter for determining the frequency of dressing cycles necessary to keep the grinding wheel's capacity to grind. Overwhelming dressing results in material waste. Whereas inadequate dressing leads to reducing the grinding wheel's grinding capabilities (Arunachalam et al., 2014).

There are currently optics-based systems for controlling the level of wheel wear (Tönshoff et

al.,2001). In order to achieve a higher-quality result for both rough and completed cylindrical traverse the sharpening process. The identification of prospective finishing factors and discovered that cross-feed rate as well as diamond geometry were the primary critical requirements (Fletcher, 1976). Acoustic emission (AE) signals were employed to track the preparation operation and create a grinding finish having a high level of consistency (Inasaki et al., 1985). Utilizing an eddy current monitor and a laser displacement detector, developed a method for determining the correct dressing frequency and the ideal wearing amount for a functioning grinding tool (Kim and Ahn, 1999). Developed a dressing procedure framework on grinding wheel interface fatigue crack observations (Torrance and Badger, 2000). To keep track of the dresser, presented an AE-dependent sensing model utilizing a neural network built upon adaptive resonance theory-2 (Egana et al., 2006). Explored employing powered devices to sense the dressing activity. There is no established method in the corporate sector for managing the topographical characteristics of a grinding wheel while it is grinding (Brzezinski et al., 2009).
Therefore, in this study, an effort is undertaken to determine the frequency of laps essential to dress the grinding wheel by employing Deep Learning (DL). Fig 2 illustrates the different types of grinding processes.

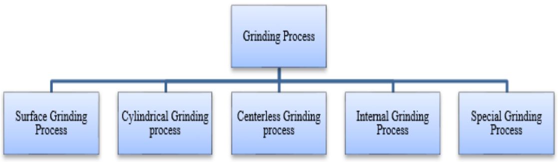

Figure 2 Types of Grinding Process

1.1 Application of the grinding process

Residual stresses could be introduced into the element by surface treatments such as water jet peening and shooting, although these methods enhance surface roughness and consequently compromise the structural integrity of the element. Precision elements must go through a finishing procedure to ensure their surface quality meets a certain standard. Now, typical finishing procedures essentially include hard turning, high-speed milling, grinding, etc. Grinding is still the primary finishing method for critical components. Grinding processes are employed in the following industries for the operations (Wang et al.,2018).

- Finishing tapered, straight, and shaped holes accurately requires the application of the internal grinding technique.
- The centerless grinding procedure.
- Milling cutters, taps, and other machine cutting tool cutters and reamers are sharpened using specialised grinders.
- The transmission bushing shouldered pins, and ceramic shafts for circulator pumps are all prepared for use.
- Cylindrical grinding is a procedure that is used to smooth the outside of circular objects.

1.2 The merits of grinding operations of the grinding process

The grinding process finds various finishing operations in automobiles, aerospace, and other different industries. The grinding process is one of the most essential operations during any manufacturing process. Products' final quality completely depends upon the process selected for finishing the surface (Wang et al., 2018). Some other advantages of the grinding process are as follows: -

- Through the grinding process, a high-quality finish and precise dimensions could be obtained.
- This technology is capable of processing extremely tough components.
- The grinding process could be carried out with minimal strain on the workpiece.
- It is capable of obtaining incredibly precise measurements.
- Extreme temps could also be used in the grinding process.
- Improves the speed at which materials are sliced.
- Self-sharpening grit granules are used in grinding.
- Applicable to both simple and complex situations.

2. Literature Review

This section discusses the work already held in the field of dressing, conditioning, and monitoring grinding wheels. The work of researchers, their approaches, and outcomes in this area are discussed in this section.
Alexandre et al., (2018) presented to assess the grinding wheel's surface regularity as well as the dressing state throughout the surface grinding procedure using fuzzy models and the digital processing of acoustic emission. Synthetic diamond dressers in a surface grinder with an aluminium dioxide grinding wheel were used for the tests. The outcomes show that the fuzzy model did a very good job of identifying the surface condition of the grinding wheel.
Yang et al. (2018) suggested a new grinding wheel

wear monitor system that is based on support vector machines and discrete wavelet decomposition. An acoustic emission (AE) sensor gathers the grinding signals. To separate the grinding phase signals from the raw AE signals, a preprocessing technique is proposed. The findings suggested that a 99.39% classification accuracy might be attained by the suggested monitoring method.

Martins et al., (2013) suggested an approach to use the acoustic emission (AE) signal to describe the dresser wear status. A few neural network models are suggested in order to do this. Eight neural network models were tested using combinations of both frequency bands as inputs, and the results were compared with the models' classification performance. It was confirmed that the frequency ranges of 28–33 as well as 42–50 kHz together best described the wear state of the dresser. The outcome showed 100% classification success.

Roth et al., (2007) suggested an overview of Tool conditioning and monitoring (TCM)in relation to milling, grinding, turning, and drilling. Which focuses on the algorithms and hardware that have proven effective in TCM for various processes. The method was found to achieve 97% clustering accuracy for the data set that contained only signals relevant to high material removal rates, 86.7% for the data set that contained only signals relevant to low material removal rates, and 76.7% for the data set that contained a mix of signals essential to both high and low material removal rates.

Liao et al. (2010) examined a wavelet-based approach based on acoustic emission (AE) signals presented for grinding wheel status monitoring. Alumina specimens were ground under two distinct conditions utilizing resinoid-bonded diamond wheels in creep feed mode studies. According to the test findings, the suggested approach could obtain a clustering accuracy of 76.7% for combined grinding settings, 86.7% for low rate of material removal conditions, and 97% for high material removal rate situations.

Nakai et al., (2015) proposed to use intelligent systems made up of four different types of neural networks to assess the wear on diamond tools during the grinding process of advanced ceramics. Intelligent systems bring about a novel component of the grinding process in conjunction with signals and data. The outcomes show that the models do a very good job of estimating tool wear.

The current study's success rate for the high material removal rate (120 lm) was 95.8%, and for the low material removal rate (20 lm), it was 96.2%, demonstrating the study's pertinent contribution.

Agarwal et al., (2013) estimated, a novel analytical model of undeformed chip thickness is used to create a new grinding force as well as power model. The suggested model and the experimental data from various kinematic situations were found to be in good agreement, according to the results.

Lin et al. (2018) evaluated the characteristics of three distinct grinding wheels' bandwidths and observed frequency conducted out over the unprocessed AE signals. Using the AE spectrum, the root means square and ratio of power statistics in various frequency bands were used to derive the transmitted signals of the material parameter variation. By looking at the study findings, it is evident that the recommended technique is effective in telling apart various grades of grinding wheel performance from every unprocessed AE pulse component.

Pandiyan et al., (2018) presented the temporal progression of abrasive grain erosion in a belt tool and the creation of a forecast categorisation technique built on Support Vector Machines and Genetic Algorithms (GA) to detect abrasive belt worn in a robotic abrasive belt grinding operation. Material surface integrity is safeguarded because of the condition-tracking forecasting method and the belt's performance.

Arun et al., (2018) presented a cylindrical grinding process equipped with an acoustic emission monitor and the associated equipment and programming for signal analysis as a test design. Acoustic signals are collected till the girding wheel's grit granules grow rough, and then they are discarded. The procedure generated a level of surface roughness obtained from the start of the grinding phase till the finish of the grinding phase at regular periods. There is indeed a high association between the acoustic emission characteristics and the grinding process's layer thickness, according to the findings.

Wang et al., (2018) suggested to gave a summary of the evolution of the surface integrity hypothesis and illustrated the important effects of surface integrity on element cyclic loading, presents the grinding procedure as a process development and data analysis condition, and provides the theoretical and practical aspects of grinding techniques with excellent surface integrity following case hardening of key components.

Tian et al., (2017) proposed to build a mobile power surveillance unit with data analysis tools specifically tailored for grinding. The software array's core purpose included information capture, extraction of features, and information processing, as well as a dataset analytics toolbox. The mobile power tracking device created is straightforward to apply in manufacturing circumstances to improve and optimize the grinding operation.

Gopan et al., (2016) stated to utilised image capture and image analysis to construct a platform for quantitatively assessing wheel loads. Magnifying glass at a sensitivity of 20x was used to take pictures of the grinding wheel. The charged areas of the wheel were isolated from the main of the image using an image separation method named global thresholding. This study showed that the suggested technology could accurately measure grinding wheel loading using observational evidence.

Moia et al. (2015) employed an Acoustic emission (AE) signal, and statistics obtained from this signal were used to supervise dressing activity, distinguishing grinding surface sharpness or dullness by employing artificial neural networks. The Levenberg–Marquardt learning technique was applied with a multilayer perceptron neural network. The findings demonstrate that this strategy worked well in distinguishing grinding wheel parameters during dressing.

Devendiran and Manivannan (2013) studied the use of intermittent waveform transforms on acoustic emission patterns and statistical collection of features for every wavelet decomposition stage, followed by classification using decision tree C4.5 data mining algorithms. The investigation demonstrated that C4.5 is an effective classification algorithm, and therefore, it is capable of effectively diagnosing grinding wheel degradation.

Wegener et al. (2011) reviewed the Economic and technological aspects of emerging and traditional conditioning systems. Research implications that the surface of the grinding wheels is an extremely important parameter as per the recent studies. Analysis of grinding wheel interface information yields reduced important values for the conditioning phase.

3. Characteristic

Cutting wheels have five distinct attributes: material of abrasive, grain diameter, grade of the wheel, spacing of grit in the wheel, and type of bonding. These five features are used to specify a grinding wheel for a different type of application (Fathima et al., 2007).

3.1 Abrasive Substance/Material

The abrasive material of a grinding wheel is denoted by an alphabet. The abrasive substance is chosen mainly based on the material getting cut's strength. Chemical stability is another issue to consider. Silicon carbide, for example, is not appropriate when used with iron-based materials such as steel. Some Abrasive substances used in industries with their abrasive symbols are Aluminum oxide (Al_2O_3) (A), Silicon carbide (S), The material ceramic (C), and Cubic boron nitride (CBN), Diamond (D) (Fathima et al., 2007).

3.2 Size of the grain

A number denotes the grain size of a grinding wheel. The overall geometric diameter of the abrasive particles within the wheel is determined by a scale of 10 for coarsest to 600 for finest. A bigger grain would cut more easily, enabling quicker cutting but with inferior overall quality. Superior finishing treatment requires ultra-fine grain sizes (Malkin et al., 2007).

3.3 Grade of Wheel

An alphabet defines the grade of the grinding wheel. The degree to which the binding retains the abrasive varies from A (soft) to Z (hard). Smoother structures range from A to H, moderately hard structures range from I to P, and hard structures range from Q to Z (Malkin et al., 2007).

3.4 Hardness of grains

Grain spacing of a grinding wheel is defined by a number from 1 (the highest density) to 17 (the sparsest) in terms of separation or architecture. The proportion of bonding and abrasive to the empty vacancy is known as density. A less dense wheel cuts more easily and has a significant impact on surface quality (Priarone et al., 2016).

3.5 Wheel-bonding

The letter that determines the connection of the wheels is called the wheel bonding letter. The finish, coolant, and minimum/maximum wheel speed are all affected by how the wheel retains the abrasives. Table 1 contains a list of some types of bonds generally used to design grinding wheels (Agarwal et al., 2013).

Table 1 Different types of bonds used in Grinding Wheel

Bond name	Bond symbol	Bond description
Metal	M	Alloy bond
Oxychloride	O	Oxyhalide bond
Plated	P	Electroless bonding of metal

Resinoid	B	Resin-based bond
Rubber	R	Rubber or synthetic rubber bond
Shellac	E	Shellac-based bond
Silicate	S	Silicate-based bond

4. Results and Discussion

The state of the grinding wheel during the grinding operation directly influences the product's dimensional accuracy. Due to the importance of machining sound variance in determining grinding wheel wear, this research uses artificial intelligence to acquire experienced operators' auditory identification and visual identification experiences. Table 2 summarized the different studies based on tool monitoring.

Table 2 Summarized the different studies of grinding tool monitoring.

Author	Sample size	Sensor	Sensing Element	Depth of cut	Technique used	Remark	Accuracy
Tönshoff et al., (2002)	820	Microphone	Sound	10µm	Deep learning	A grinding machine microphone was used to gather audio signals while the machine was being ground.	97.44%`
Ding et al., 2014	-	Dial Gauge	Pressure	-	ANFIS, GRP &Taguchi Analysis	Analyses have shown that the ANFIS-GPR hybrid algorithm-based prediction system is very intelligent.	98%
Devendiran and Manivannan (2013)	24	Microphone	Sound	30,20,10 µm	Wavelet Analysis, Decision Tree C4.5 Algorithm	Experimentation has shown that C4.5 is an effective classifier and that it could precisely assess grinding wheel wear.	95.25
Yang et al., (2018)	33	Microphone	AE	-	DCNN	Researchers find out aspects of grinding noises that are sensitive to belt wear.	82.2%
Tönshoff et al., 2002	560	Image Sensor (Camera)	Image	-	Support Vector Regression (SVR) and Machine Learning	Results reveal that the predicted tool condition and the actual tool condition are sufficiently similar, with an R^2 of 0.9590 based on a support vector regression model.	95.90%
Pandiyan et al., (2018)	26	Force Sensor and Microphone	Acoustic Emission and Force	-	SVM and GA	Abrasive belt condition states may be predicted with great accuracy using this research's SVM-based in-process tool condition monitoring model, as shown by the experimental findings.	94.7%
Gopan et al., (2016)	-	Microscope	Image	0.1 mm	Image segmentation by a global thresholding technique	The cutting surface of the wheel could be seen in images taken at a magnification of 20x. According to the findings of the research, chip accumulation increases with time.	-
Chen, et al., (2018)	300	Microscope	Image	-	Random forest classifier (RFC) and a multiple linear regression (MLR) model	This Technique may be used in advanced manufacturing for precision machining complicated workpieces.	90%
Subrahmanya r et al., (2008)	-	Microphone	AE	10 to 200 µm	Machine Learning	The machine's sensors allow it to monitor cutting forces and surface roughness.	99%

A study of the different techniques used to detect the surface roughness of grinding machine has been done on the basis of their efficiency. Different authors used different techniques to detect the surface roughness, as shown in Fig 3. The deep learning to monitor tool conditions and achieve an efficiency of 97.44% was used by Tönshoff et al.. Their study was based on the detection of acoustic emissions. Ding et al. used ANFIS, GRP, and Taguchi Analysis and used the pressure as a sensing element to detect the tool condition and achieved an efficiency of 98%was used by Ding et al. The “wavelet analysis” and “decision tree C4.5 algorithm” achieved an efficiency of 95.25% by sensing the machining sound used by Devendra and Manivannan.

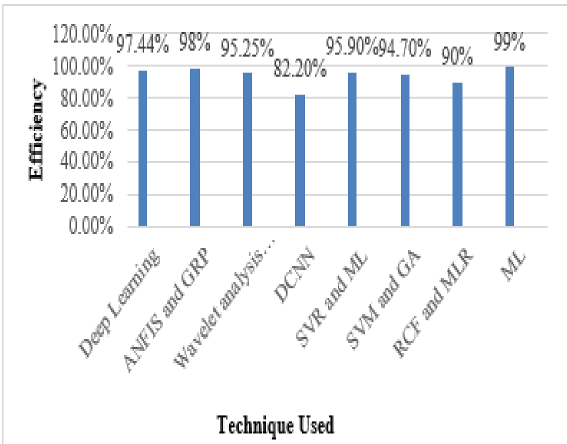

Figure 3 Summary of different studies

The DCNN achieved an efficiency of 82.20% was used by Yang et al. used. Tönshoff et al. used SVR and ML and achieved an efficiency of 95.90% was used by Tönshoff et al. The SVM and GA and achieved and efficiency of 94.70% was used by Pandiyan et al., . Oo et al., uses RCF and MLR and achieved an efficiency of 90% was used by Oo et al., . The ML and achieved an efficiency of 99% was used by Subrahmanya et al.

5. Conclusion & Future Scope

The focus of ongoing research has been on grinding at very high speeds and efficiency. The grinding tolerance should be kept to a minimum due to the shallowness of the residual stress layer formed by the surface treatment operation. When it comes to single grinding, the depth must be properly controlled. This review looked at several intelligent systems for monitoring the status of grinding wheels based on “machining sound”, DL, machine learning, and image processing, out of which ML Techniques seem to be most efficient. The result of this review is majorly concentrated heavily on studies that employed machining sound (acoustic emission) to gather acoustic signals during the process. For this purpose, a microphone was integrated into the machine to collect acoustic data. For grinding wheel condition analysis, feature extraction was done to find out which features are most discriminating from the others. More data on various grinding settings and on-site environmental conditions would be gathered in the future to improve the system's stability and resilience. The following highlighted points are the paper's primary contributions:

- Comparison with past grinding wheel wear research shows that the approach used is successful in classifying data and could be competitive when compared to previous studies, which used numerous samples.
- This review's findings indirectly suggest that AI techniques may draw on the auditory experiences of older operators to assess the tool's attired state based on changes in sound throughout the machining operation. It's anticipated that this paper would serve as yet another useful example of tool wear monitoring in action.

Policymakers may utilise the suggested machine learning-based prediction model to monitor the grinding wheel's condition during its operation. With the information supplied by the framework, it is possible to decide whether to replace the grinding wheel with a new one or to submit it to a dressing operation. The quality of the finished product is guaranteed, as well as significant savings in terms of money and time. As a result of this review, an online grinding monitoring system using acoustic emission signals would be very helpful. Consequently, additional grinding input parameters and an optimised feature space with a classifier combination would be added to the system to make it more resilient for further implementation. Noise filtering methods could be used to further reduce the number of errors in data processing.

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