Available online at www.sciencedirect.com

ScienceDirect

Procedia Manufacturing 38 (2019) 840–847

Procedia MANUFACTURING

www.elsevier.com/locate/procedia

29th International Conference on Flexible Automation and Intelligent Manufacturing (FAIM2019), June 24-28, 2019, Limerick, Ireland.

Remote acoustic analysis for tool condition monitoring

James Coady[,b], Daniel Toal[a,b], Thomas Newe[a,b], Gerard Dooly[a,b]

[a]*Centre of Robotics & Intelligent Systems, University of Limerick, Ireland*
[b]*Confirm Research Centre, University of Limerick, Ireland*

Abstract

Within the manufacturing industry, predictive maintenance is a well-established concept, dating back to the 1990's [1]. Practice has shown it to have a proven track record of minimising unnecessary machine downtime. The methods of predictive maintenance have varied widely, including visual inspection (i.e. human monitoring), thermal imaging, ultrasonic analysis, vibration analysis, power consumption, acoustic emission, to name a few. As manufacturing technologies have developed, maintenance in general has become a more complex task, presenting many challenges for researchers, engineers and scientists. These challenges have been met through research and development of new technologies and methods of maintenance.

Some of these methods currently involve installing intricate sensor systems which are placed on, or in close proximity to the system under test (SUT). Although some of these monitoring methods have been slow to catch on within industry, much of the reason for this can be accredited to the high cost of these sensors along with the high probability of damage to and the replacement of them. Practice is now moving towards using remote monitoring systems (RMS) as a possible method to reduce some of these issues. This is due to the ability to carry out monitoring without having to install the monitoring system on the structure of the SUT, hence minimising the potential for damage to the sensor systems.

This paper aims to describe the importance of predictive maintenance (PdM) over other maintenance methods (e.g. reactive, corrective etc.), the importance of PdM for the metal cutting industry (focusing on cutting tool wear), while also discussing some common methods of predictive maintenance monitoring system methods already being utilised within industry. The final method discussed is remote monitoring systems used to monitor transmitted sound, while also identifying how this monitoring system could be integrated within the smart manufacturing environment that is being driven by Industry 4.0.

2351-9789
This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/)
Peer-review under responsibility of the scientific committee of the Flexible Automation and Intelligent Manufacturing 2019 (FAIM 2019)
10.1016/j.promfg.2020.01.165

Keywords: Predictive Maintenance (PdM); Remote Monitoring System (RMS); Tool Condition Monitoring System (TCMS); Tool Wear

1. Introduction

There is a clear and concise goal to any maintenance organisation, to maximise asset availability, which as a result aids in maintaining and increasing performance and product output [2]. Traditionally, organisations have made the decision to run many of their plant machinery until failure and subsequently carry out maintenance as required. However, with the continuous advancements in manufacturing processes and the increasing complexity of machinery, maintenance teams face new challenges. It has now become the case that it is not cost efficient to allow important machinery to run to failure, as by doing so could cause catastrophic damage to the machinery due to excessive vibration, overheating, breaks of parts etc. not to mention loss of business due to lack of orders and possible injury to personnel [3].

1.1. Penetrative and predictive maintenance

To avoid unwanted machine downtime or component failure, maintenance would traditionally be scheduled at intervals that vary depending on the importance of the machinery and the manufacturing processes being carried out (this is known as preventative maintenance). However, this method of maintenance requires many resources and can become very costly to the company (i.e. preventative maintenance does not ensure that the machinery will not breakdown outside of these scheduled maintenance times) [3]. A solution to this was to replace machine components more frequently with the hope of avoiding unwanted failures, however, this again would cause an uplift in company costs over time and increased planned downtime to machinery. Also due to more frequent part replacement, it then puts a more significant strain on the stocking management as they must now hold more parts in stock at any one time [4][5].

With the constant growth on the importance of maintenance within the industrial sectors, engineers and scientists have now moved from Corrective/Preventive maintenance to Predictive maintenance (PdM) [6]. PdM not only aids in avoiding unwanted or unexpected machine downtime, it is also found to be a more efficient and cost-effective method of maintenance. Analysts have found that poor plant maintenance strategies harm a plant‘s productive capacity, reducing it between 5 to 20%. However, by having an effective maintenance system in place, machine uptime can be increased [2]. Having an effective maintenance system in place that requires little resources not only increases machine productivity, but it is also essentially ‘free money’ to the company [3].

There is a wide range of PdM methods currently in place within the machining industry to monitor tool wear such as; vibration analysis, visual inspection (human inspection), power consumption, acoustic emission and sound analysis. Many of these methods currently involve installing intricate sensor systems which are placed on, or nearby the system under test (SUT). However, with the high probability of damage to these sensors, which will result in high costs to constantly replace them, installing a remote monitoring system can help reduce many of these issues as it allows for protection to the valuable sensor systems [7][8].

This paper discusses some common methods of PdM, their capabilities and limitations (with an emphasis on tool wear), while also exploring how a remote system might overcome some of these limitations. Also discussed within this paper is tool wear and how these remote systems could be incorporated into flexible, smart manufacturing environments that are currently being driven by Industry 4.0.

2. Metal cutting & cutting tools

Current information from the Central Statistics Office (CSO) Ireland shows that in 2016, the percentage of production from the metal cutting industry stood at 4.2%. These statistics represent fabricated parts that do not end up serving as a part of a machine or the production of a machine itself. It is worth noting the quantity of machinery that runs the pharmaceutical industry, which in turn makes up for 43.7% of production [9]. These factors drive the need for metal cutting organisations to ensure their machining processes and product output performances are kept to a high standard to ensure growth and profit within the company. The monitoring and maintenance of the health of machinery and the machine components (such as the cutting tool) are also of great importance as all of these factors have an impact on the finished products [10].

2.1. Tool wear

A cutting tool is any tool that is used for the removal of material from a workpiece. Cutting tools are used in a variety of machinery such as lathes, grinding wheels, milling machines etc. (both manual and automatic). They can generally be divided into two categories; single point (i.e. turning, shaping and planning operations) or multipoint tooling (i.e. milling and drilling operations). For the cutting process to be carried out, the tool must be harder than the material it is intended to cut [10][11].

As cutting operations are playing such a major role in current industrial manufacturing (allowing for high speed and accurate machining of large to small complex parts), tool degradation monitoring is of great importance during machining processes as it dictates the quality of the finished surface, the dimensional accuracy of the cut and the power required to carry out the process (resulting in increased carbon emissions), along with large investments in the replacement of expensive cutting tools due to breakage [12][13]. Tool wear depends on several factors; the material being machined, the nature of the tool and the type of machining process being carried out (e.g. drilling, milling, turning etc.) [14]. However, there any many other factors that come into play; the spindle speed, cutting tool feed rate, coolant rate, type of coolant used (oil, water etc.) also must be considered [15][13]. The use of coatings has also been found to extend tool life. Coatings increase the tools surface hardness while having a number of other advantages such as decreasing friction between the tool and part being machined and allowing for better surface temperature distribution by dissipating heat generated during machining, allowing for tool quality to remain for a longer state [13][16].

There two main types of tool wear; Flank Wear and Cratering (See Figure 1 for illustration of these types of tool wear). Flank wear is the abrasive wear of the tool cutting edge surface that is parallel to the work piece, generally caused by; friction between the tool and the part, abrasive actions of the microchips and diffusion. An increase in flank wear leads to a rise in the vibration of the tool and a higher amplitude of sound being emitted while machining. With the increased vibration of the cutting tool, this leads to dimensional accuracies not being met along with damage to the tool and other machine components [17][12]. Cratering typically occurs in high-temperature, high pressure machining processes. This high temperature and pressure create a constant chip flow across the rake surface of the tool, causing the tool material to diffuse or dissolve into the chip [14]. These welds then begin to be knocked off the tool, taking part of the cutting tool with them and leaving divots in the tool rake which become more significant over time. Cratering results in poor surface finish and requires immediate tool replacement [7]. Figure 1 illustrates the effects on a cutting tool if placed in improper machining conditions.

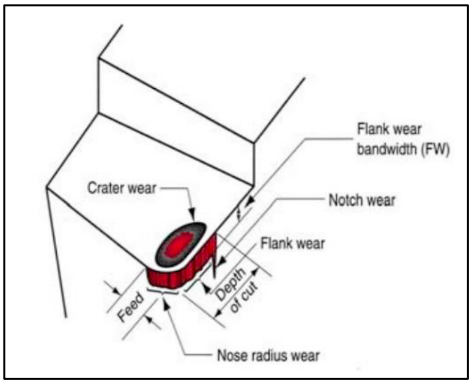

Figure 1 Effects on Cutting Tool in Improper Machining Conditions [20]

3. Common tool condition monitoring methods

There are various methods used within industry to monitor tool wear and these can be broken down into direct and indirect sensing methods. Optical scanning, radioactive techniques and measurement of tool geometry are examples of direct sensing. This section will cover both vibration monitoring and acoustic emission which both fall under indirect sensing methods [19].

3.1. Vibration analysis

This method of condition monitoring is generally used on rotating and/or reciprocating machinery and can be carried out by using a hand-held device or by installing sensors onto the SUT [20][21]. If a mechanical system is designed correctly, vibration within these machine components are kept at a safe, normal level. However, if these systems are not adequately monitored and maintained, these vibrations will begin to increase due to misalignment, worn gears, unbalanced forces, looseness etc., resulting in both fatigue and catastrophic failure to components [22][23]. Vibration levels are measured using sensors, the most common sensor being accelerometers. Accelerometer sensors are mounted onto the SUT, measuring the vibration of a machine and outputting a current or voltage proportional to the vibration and relative to a 'g' level (unit of gravitational pull) [24].

There has been much research (dating back to the 1980s) into the analysis and control of vibration within cutting tools [25]. Some recent studies have shown the following results:

- Depth of cut and cutting speed are the most significant parameters for controlling vibration [25].
- Vibration in cutting tools during dry turning increase as spindle speeds increase, and vibration decreased as the depth of cut rises (at the same rpm) [25].
- Tool geometry, the hardness of the material being machined and cutting parameters affect both the vibration signals produced and tool wear directly [26].

However, as previously noted, the main limitation to this monitoring method is the possibility of damage to the sensors. Some other limitations encountered are extracting the vibration effectively without allowing factors such as coolant/lubricant and noise signals interfere with the extracted vibration signal [27].

3.2. Acoustic emission

Acoustic emission (AE) monitoring differs slightly from transmitted sound monitoring methods (i.e. for remote acoustic analysis monitoring systems) as it uses sensors that are placed on the SUT. During metal cutting processes, the part being machined will begin to deform as the cutting tool removes material. This deformation process generates elastic waves due to the rapid release of energy from sources within the material (this is known as acoustic emission). AE is one of the most effective methods for the monitoring of tool wear [21]. Other AE sources are due to the microchipping of the tool surface, microcracks in the material and the interaction of surface asperities between the tool and the material [28][29].

For identifying tool conditions, AE methods have been found to be very accurate and focus on identifying only significant defects that are actively growing under stress. However, this method does come with its limitations. AE signals are high frequency and low amplitude with a broad frequency range (100kHZ to 2MHz). Because of this, as the distance from the sound source and the sensor increases it can result in quick attenuation of the signal which can result in reflection of the signals and possibly allow other undesirable noise elements being introduced into the measured data [7][21]. By mounting these sensors directly to the workpiece, this can be an effective alternative method in high precision machining operations as it reduces the distance between the sensor and the source. However, since these sensors require installation on each workpiece, it causes a 'halt' to process cycle time, making high volume production a much more onerous task. The most notable limitation (aside from damage to the sensors) is that while AE sensors have a broad frequency band, this brings the necessity for large computing power due to the processing involved, this however, has shown that AE sensors are incredibly versatile due the choice of monitoring conditions available for collection and analysis [30].

3.3. Challenges facing current monitoring methods

Recent advances in micro-machining processes have indirectly led to a need for a useful TCMS. Some of this is due to the increase of hardness in cutting tools used during micro-machining. As hardness is accompanied with brittleness, this has led to the use of smaller, more fragile cutting tools essential for machining to extremely tight tolerances. Having to re-machine parts or replace the fragile cutting tools will not only cause an uplift in costs for an organisation, it can also have a negative effect on their reputation within industry [31][16]. Due to these cutting tools becoming smaller and more fragile, it is also becoming a much more onerous task to find space to mount the sensors on or near them, confirming that a remote system could be far more desirable to implement into a PdM system.

4. Remote acoustic analysis monitoring

While transmitted sound is generated by the same sources as AE, one of the primary advantages of this method is that it can be installed remotely, which is desirable, especially for micro-machining processes and in very harsh industrial environments [7]. As research into this area has slowly progressed, the primary concern with the use of microphones to monitor tool wear is focused on how to extract the signal produced from the machining operation from the background noise. The use of signal processing, sensing systems and intelligent decision systems has been incorporated to address this issue [32]. The use of both single and array microphone systems must be addressed to ensure the selected system is fit for purpose.

The most common method used to measure sound signals produced by tool wear has been with the use of a single microphone. However, this method cannot detect the direction of the sound it picks up as it receives sound from the entire environment or space. The placement of this single microphone is also of great importance as if it is placed too close to the SUT, near-field effects will affect the measured signal [33][34]. There are two approaches to using microphone arrays: near-field (acoustic holography) and far-field (beamforming). Both methods allow an image to be created of the sound generated in that area. This image can then be overlaid onto a 2D photograph or 3D computer model of the area (i.e. factory floor). These array systems allow the required sound sources to be located in a space, reducing background noise which has traditionally been a great issue. The process is then carried out by evaluating the entire data collection, then focusing on the area of interest [7][35]. By allowing specific areas to be focused on, this system then becomes more flexible as it is not designed to be 'fit for one purpose'. When required, it can then be used to monitor various machinery on the factory floor and compare the collected sound signals to a specific dataset to allow for future faults to be predicted. For this reason, the remote systems have a great possibility of being integrated effectively into smart manufacturing environments.

Other applications of remote monitoring of transmitted sound include but are not limited to; Monitoring airborne sound emitted during cut-off grinding of concrete with diamond grinding disks that allow to monitor parameters such as tool deflection and friction forces [36]. Remote acoustic sensing is not only limited to manufacturing/machining processes, studies have shown its use in oceanology to monitor temperature and flow fields in shallow seas [37]. This again shows the flexibility of these monitoring systems].

4.1. Data Collection

For a remote TCMS to be incorporated into a smart manufacturing environment, it is essential to identify the specific data that is required to be collected, the methods utilised to acquire this data along with specifying as to what actions are to be taken with the gathered data once it is collected [7].

During a machining process, sound signals will be picked up by a microphone (or microphone arrays), this data will then be sent through the systems central processing unit (CPU) to process it into readable data for analysis. This stage may also include amplifying the signal, filtering (to reduce the background noise), segmentation and an A/D conversion [7]. Data is then sent to the cloud for a cross-analysis between the measured signal and recorded signals to find a match. Once the analysis is complete, an actuation (such as an alarm to the technician warning of imminent tool failure) is sent back to the CPU. The sound signature is then recorded for future use [38]. The decentralisation of these tasks will allow for the freeing up of local server space which can in turn open up this unused space to be used as a production environment [39].

4.2. Industry 4.0 & potential applications

The new industrial revolution (Industry 4.0) is the fourth major revolution since the initial industrial revolution that began circa 1800s. The first industrial revolution refers to the development of the steam engine, the second revolution was the introduction and use of electric power to create mass production and the third marked the beginning of industrial automation. Industry 4.0 is the first planned revolution, aiming to push the manufacturing industry towards the digitisation of processes, products and production facilities. The objective of technologies such as the industrial internet of things (IIoT), big data and cloud computing is to connect all of these systems to allow for the gathering and analysis of data in real time (allowing the manufacturing systems to be continuously provided with useful information to optimise their processes) [38][40]. This can be summarised as a digital twin of products and processes.

A digital twin is a digital copy of real-world conditions stored as data, normally in the cloud [41]. This is made possible through the utilisation of cyber-physical systems (CPS). A CPS is a physical element of a manufacturing system (either a product or component), which possesses its own sensing, actuating and local computing power. A CPS allows real-time data gathering from the physical world which can then be compiled to form a digital twin of the process or product [39]. Remote acoustic monitoring would allow for the collection of data in a CPS specific to sound signatures. This would present opportunity for the mapping of the ideal sound profile of a process. These sound profiles would then contribute to a larger data set. Machine learning can then be used to compare real-time detected sounds produced during processes to this dataset and thus identification of specific problems or challenges in real-time is possible. This will allow for smart manufacturing as it allows for possible catastrophic component failures to be known before these issues occur [42].

The use of big data and cloud computing for the analysis and storage of the acoustic signals, error messages, failures etc. is vital for a predictive maintenance team as it can ensure that cutting tool health is monitored effectively. An effective monitoring system also ensures that failures etc. are caught well in advance, safeguarding that the machining process is carried out without any unwanted issues and that the finished product is produced to set standards, tolerances etc. By gathering and storing this data and creating trends, this allows correlations to be drawn. These correlations can be employed for predictive outcomes across similar machine, tooling or process types [38].

Remote acoustic analysis is not just limited to monitoring of cutting tool wear. There are numerous applications within industry such as motor and bearing monitoring, to name a few. As motor windings begin to wear, the motors produce specific sounds that can be collected and analysed to predict failure of the motor or a component within the motor. The wear and failure of bearings could also be monitored using these remote systems [43]. Faults within bearings have been found to have different sound and vibration frequencies depending on the fault. For example, as the rolling elements of a bearing strike a fault on the inner or outer race, this produces a specific impact (or sound) which can be detected, and an alarm signaled to specify that a bearing change is required [44].

5. Discussion & conclusion

The aim of this paper was to give a brief overview of the importance of PdM some common methods of PdM, the advantages and limitations of each, while also exploring the advantages of using a RMS to analyse acoustic signals generated from cutting tools during machining processes. While common methods such as vibration analysis and acoustic emission monitoring have been used extensively and successfully within industry, the general requirement for these systems to have sensors installed on the structure of the system, or on the workpiece itself, has presented the issue of a high probability of damage to the sensors involved (leading to high costs to install and replace them)[7].

As can be seen from the literature presented, a RMS has the ability to reduce and, in some cases, eliminate these issues. With an acoustic analysis RMS, the main issue for concern is filtering out background noise and extracting the desired sound signals produced from the machining process. Also, by having a remote system, access and maintenance to the monitoring system is a much easier task while also being non-disruptive is non-disruptive (i.e. it will not disturb machining processes) [30][7].

The use of single and array microphone systems has been explored, and it has been found that although single microphone systems are more commonly used for tool wear detection, they are limited due to the inability to locate the sound source [33][34]. Array microphone systems have the ability to detect the required sound source by producing an acoustic image of the area and overlaying this on a 2D photograph or a 3D model of the area (factory floor for example). Array systems use two methods to create an image of the sound generated within a space; near-field (acoustic holography) and far-field (beamforming) techniques. Near-field holography requires the microphones to be placed within a short distance to the system that is being monitored, effectively removing the advantage of remote monitoring. Far-field beamforming systems must be placed at a long distance from the system being monitored so as to gather sounds from a large surface to allow an effective acoustic map to be produced and the required sound source to be extracted [7][35].

For these systems to be incorporated into smart manufacturing environments (working towards of Industry 4.0), it is important to briefly touch on the methods that could be used to gather the necessary information from the sound signals, the processing of these signals and how the analysis and storage of this data can be used for future use. IoT, big data and cloud computing will play a huge role in this as they allow for all processes, products and manufacturing systems to be interconnected in order to optimise machining processes [38].

Acoustic analysis is not just limited to tool wear monitoring. Fault diagnostic techniques for mechanical faults of bearings, rotor shafts, motor windings etc. are just a few of the wide variety of applications for these systems within industry [43][44]. Although acoustic analysis can be employed to these applications, there are research and sensor implementation challenges that must be addressed to make use of acoustic analysis as an effective tool for the digitisation of a manufacturing process, leading to Industry 4.0.

Acknowledgements

This work was supported by the Science Foundation Ireland under Project 16/RC/3918. Also supported by the European Regional Development Fund and Ireland's European Structural and Investment Funds Programmes 2014-2020.

References

[1] M. Arifpin Mansor and S. Sulaiman, "Knowledge Management for Maintenance Activities in the Manufacturing Sector," *Article in International Journal of Automotive and Mechanical Engineering*, 2012.
[2] G. Wollenhaupt, "IoT Slashes Downtime with Predictive Maintenance — PTC," 2016.
[3] C. Coleman, S. Damofaran, and E. Deuel, "Predictive maintenance and the smart factory," *Deloitte*, p. 8, 2017.
[4] H. Hashemian, "Wireless sensors for predictive maintenance of rotating equipment in research reactors," *Annals of Nuclear Energy*, vol. 38, pp. 665–680, feb 2011.
[5] I. Connection Technology Center, "Industrial Vibration Analysis for Predictive Maintenance and Improved Machine Reliability," tech. rep.
[6] N. Sakib and T. Wuest, "Challenges and Opportunities of Condition-based Predictive Maintenance: A Review," *Procedia CIRP*, vol. 78, pp. 267–272, jan 2018.
[7] V. G. Cook, "Acoustic Monitoring of Machine Tool Health Using Transmitted Sound," in *Industrial Engineering and Operations Management Istanbul*, pp. 1831–1839, 2012.
[8] M. Mori and M. Fujishima, "Remote monitoring and maintenance system for CNC machine tools," *Procedia CIRP*, vol. 12, pp. 7–12, 2013.
[9] Central Statistics Office (CSO), "Irish Industrial Production by Sector," tech. rep., 2017.
[10] M. A. Elbestawi, "METAL CUTTING THEORY AND PRACTICE," *Machining Science and Technology*, vol. 2, pp. 383–384, dec 1998.
[11] Metal Cutting Tool Institute., *Metal cutting tool handbook.* Published for the United States Cutting Tool Institute by Industrial Press, 1989.
[12] Z. T. Tang, Z. Q. Liu, Y. Z. Pan, Y. Wan, and X. Ai, "The influence of tool flank wear on residual stresses induced by milling aluminum alloy," *Journal of Materials Processing Technology*, vol. 209, pp. 4502–4508, 2009.
[13] R. Gouveia, F. Silva, P. Reis, A. Baptista, R. M. Gouveia, F. J. G. Silva, P. Reis, and A. P. M. Baptista, "Machining Duplex Stainless Steel: Comparative Study Regarding End Mill Coated Tools," *Coatings*, vol. 6, p. 51, oct 2016.
[14] A. Devillez, S. Lesko, and W. Mozer, "Cutting tool crater wear measurement with white light interferometry," *Wear*, vol. 256, pp. 56–65, 2004.
[15] M. Kuntoglu and H. Sa˘ glam, "Investigation of progressive tool wear for determining of optimized machining parameters in turning,"˘ *Measurement*, vol. 140, pp. 427–436, jul 2019.
[16] R. Martinho, F. Silva, and A. Baptista, "Cutting forces and wear analysis of Si3N4 diamond coated tools in high speed machining," *Vacuum*, vol. 82, pp. 1415–1420, aug 2008.
[17] K. Zhu and Y. Zhang, "A generic tool wear model and its application to force modeling and wear monitoring in high speed milling," *Mechanical Systems and Signal Processing*, vol. 115, pp. 147–161, jan 2019.

[18] G. Zhao, Z. Liu, Y. He, H. Cao, and Y. Guo, "Energy consumption in machining: Classification, prediction, and reduction strategy," *Energy*, vol. 133, pp. 142–157, aug 2017.

[19] R. Mali, M. Telsang, and T. Gupta, "Real Time Tool Wear Condition Monitoring in Hard Turning of Inconel 718 Using Sensor Fusion System," *Materials Today: Proceedings*, vol. 4, pp. 8605–8612, jan 2017.

[20] A. Khadersab and S. Shivakumar, "Vibration Analysis Techniques for Rotating Machinery and its effect on Bearing Faults," *Procedia Manufacturing*, vol. 20, pp. 247–252, jan 2018.

[21] N. Ambhore, D. Kamble, S. Chinchanikar, and V. Wayal, "Tool Condition Monitoring System: A Review," *Materials Today: Proceedings*, vol. 2, pp. 3419–3428, jan 2015.

[22] M. Vishwakarma, R. Purohit, V. Harshlata, and P. Rajput, "Vibration Analysis & Condition Monitoring for Rotating Machines: A Review," *Materials Today: Proceedings*, vol. 4, pp. 2659–2664, jan 2017.

[23] R. P. Martinho, F. J. G. Silva, C. Martins, and &. H. Lopes, "Comparative study of PVD and CVD cutting tools performance in milling of duplex stainless steel," *The International Journal of Advanced Manufacturing Technology*, pp. 1–17, 2019.

[24] Z. Peng and N. Kessissoglou, "An integrated approach to fault diagnosis of machinery using wear debris and vibration analysis," *Wear*, vol. 255, pp. 1221–1232, 2003.

[25] S. Swain, S. Chattarjee, I. Panigrahi, and A. K. Sahoo, "Cutting tool vibration analysis for better surface finish during dry turning of mild steel," *Materials Today: Proceedings*, vol. 5, pp. 24605–24611, jan 2018.

[26] P. Waydande, N. Ambhore, and S. Chinchanikar, "A Review on Tool Wear Monitoring System," *Journal of Mechanical Engineering and Automation*, vol. 6, no. 5A, pp. 49–53, 2016.

[27] K. Feng, P. Borghesani, W. A. Smith, R. B. Randall, Z. Y. Chin, J. Ren, and Z. Peng, "Vibration-based updating of wear prediction for spur gears," *Wear*, vol. 426-427, no. January, pp. 1410–1415, 2019.

[28] I. Marinescu and D. A. Axinte, "A critical analysis of effectiveness of acoustic emission signals to detect tool and workpiece malfunctions in milling operations," *International Journal of Machine Tools* & *Manufacture*, vol. 48, pp. 1148–1160, 2008.

[29] M. P. Gomez, A. M. Hey, and J. E. Ruzzante, "Assessment of cutting tool condition by acoustic emission,"´ *Procedia Materials Science*, vol. 1, pp. 321–328, 2012.

[30] R. Teti, K. Jemielniak, G. O'donnell, and D. Dornfeld, "Advanced monitoring of machining operations," *Manufacturing Technology*, vol. 59, no. 2, pp. 717–739, 2010.

[31] A. Colpani, A. Fiorentino, E. Ceretti, and A. Attanasio, "Tool wear analysis in micromilling of titanium alloy," *Precision Engineering*, apr 2019.

[32] S. Takata, J. Ahn, M. Miki, Y. Miyao, and T. Sata, "A Sound Monitoring System for Fault Detection of Machine and Machining States," *CIRP Annals*, vol. 35, pp. 289–292, jan 1986.

[33] F. Jacobsen and V. Jaud, "Statistically optimized near field acoustic holography using an array of pressure-velocity probes," *The Journal of the Acoustical Society of America*, vol. 121, no. 3, pp. 1550–1558, 2007.

[34] J. Hald, "Fast Wideband Acoustical Holography Evaluation of SPC and BSS for Indoor Pass-by Noise Contribution Analysis," tech. rep., 2015.

[35] D. Salgado and F. Alonso, "An approach based on current and sound signals for in-process tool wear monitoring," *International Journal of Machine Tools and Manufacture*, vol. 47, pp. 2140–2152, nov 2007.

[36] L. Robben, S. Rahman, J.-C. Buhl, B. Denkena, and B. Konopatzki, "Airborne sound emission as a process monitoring tool in the cut-off grinding of concrete," *Applied Acoustics*, vol. 71, pp. 52–60, jan 2010.

[37] V. A. Akulichev, V. V. Bezotvetnykh, A. V. Burenin, E. A. Voytenko, S. I. Kamenev, Y. N. Morgunov, Y. A. Polovinka, and D. S. Strobykin, "Remote acoustic sensing methods for studies in oceanology," *Ocean Science Journal*, vol. 41, pp. 105–111, jun 2006.

[38] M. Obitko and V. Jirkovsky, "Big Data Semantics in Industry 4.0," in´ *Proceedings of the 7th International Conference on Industrial Applications of Holonic and Multi-Agent Systems - Volume 9266*, pp. 217–229, Springer-Verlag New York, Inc., 2015.

[39] A. O. Riordan, J. Coady, T. Newe, and G. Dooly, "Industry 4 . 0 : Pillars for Smart Manufacturing – A Review," no. February, 2019.

[40] F. Alejandro German, L. S. Dalenogare, and N. F. Ayala, "Industry 4.0 technologies: Implementation patterns in manufacturing companies,"´ *International Journal of Production Economics*, vol. 210, pp. 15–26, apr 2019.

[41] S. Boschert and R. Rosen, "Digital Twin—The Simulation Aspect," in *Mechatronic Futures*, pp. 59–74, Cham: Springer International Publishing, 2016.

[42] E. Davies, *Computer Vision*. Roya Holloway, University of London, UK: Elsevier, 5th ed., 2018.

[43] L. Weidong and C. K. Mechefske, "Detection of Induction Motor Faults: A Comparison of Stator Current, Vibration and Acoustic Methods," *Journal of Vibration and Control*, vol. 12, pp. 165–188, feb 2006.

[44] R. Ellis, J. Tutcher, T. Kono, Z. Zhang, W. Driscoll, S. Bayram, C. Roberts, E. Stewart, G. Yeo, and M. Entezami, "Acoustic Analysis Techniques for Condition Monitoring of Roller Bearings," in 6th IET Conference on Railway Condition Monitoring (RCM 2014), pp. 5.1.3–5.1.3, Institution of Engineering and Technology, 2014