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Acoustic Monitoring of Machine Tool Health Using Transmitted Sound

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Abstract

Tool condition monitoring systems (TCMS) have approached detection of tool wear over time from several perspectives: visual inspection, vibrational analysis, acoustic emission, power consumption and sound analysis. Current research focuses on monitoring methods involving expensive and complex sensor systems placed in close proximity to the machining operation itself. Understandably, industry has been slow to adopt these methods due to the initial high cost of sensors and the risk of damage to those sensors in the industrial environment. Methods that can monitor industrial machining processes from more remote locations would allow protection of valuable sensor systems and involve simpler installations. Researchers have established a significant relationship between tool wear and the sound signature of machine tools, yet there has been little work in developing this into a workable application. Issues encountered by researchers focus mainly on separating background noise from the noise of the tool itself, and methods to automate the recognition of tool wear conditions in sound signatures. This paper reviews the current state of research in the sound monitoring of tool condition in machine shops.

Keywords
Condition-based monitoring, tool wear, acoustics, sound analysis (Three to five keywords related to the main topic)

1. Introduction
Tool wear is an important characteristic for monitoring in machining processes because it dictates the quality of surface finish, the dimensional accuracy of the cut and the amount of power required to remove metal. Cutting tool wear can be characterized as either flank wear, or cratering. Any tool condition monitoring system must be able to demonstrate correlation with one or preferably both of these wear mechanisms.

Flank wear is the direct abrasive wear of the cutting edge surface parallel to the work piece. It is measured by visually inspecting the tool flank surface using a measuring microscope. As a tool wears, the flank wear land (*Vb*) becomes broader as shown in Figure 1. The wear land is the most common measurand for evaluating flank wear and indicates the distance between the original cutting edge and the limit of the wear land (the bright scored section of the flank between the two lines). As flank wear increases, there is more vibration in the tool and higher amplitude sounds are emitted from the cutting site. Significant amounts of wear can result in chattering which induces significant vibration and dimensional instability. Because of the more predictable progression of flank wear and its correlation to sound and vibration, many TCMS researchers focus on this type of wear in their studies. However in actual practice, both flank wear and cratering are common mechanisms.

Cratering is a wear mechanism in which pits are formed in the rake face of the cutting tool, which is perpendicular to the work piece. According to Devillez et al. there are three mechanisms cause cratering: simple abrasion, micro-welding, and diffusion. Generally cratering is found in cutting processes where heat is significant and many studies have evaluated the relationship between coolants and crater development in tools. Craters are typically evaluated by depth (K_t) and distance to the cutting edge (K_m). Figure 2 shown an example of cratering in a rake face and the measurements [2]. Micro-welding occurs when the cutting process heat actually causes the chips to weld themselves to the tool. The welds are periodically knocked off the tool taking some parent metal with them. This leaves divots in the tool rake which enlarge with time. Ultimately, the crater becomes so large that it “breaks-through” creating a jagged edge, typically near the nose of the tool. This break-through causes poor surface finish and requires immediate tool replacement. The challenge in detecting cratering is that its acoustic characteristics are not the same

as those generated by flank wear. A crater “break-through” produces a positive rake on the cutting surface which results in a drop in cutting force and a corresponding drop in the amplitude of sound or vibration generated [3]. The non-linearity of the effects of cratering makes its indirect monitoring difficult and has not been the focus of much research.

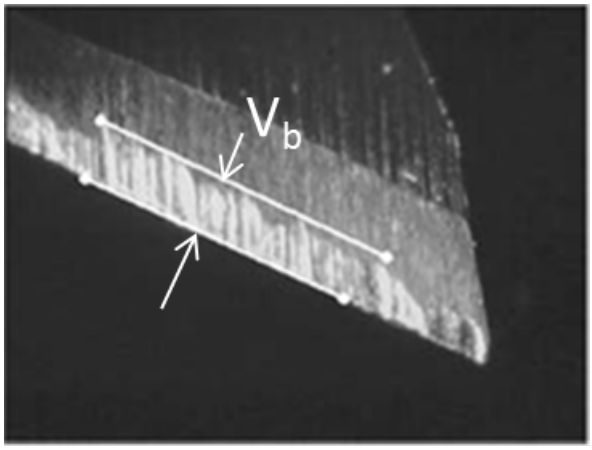

Figure 1: Flank Wear Land Measurement[1]

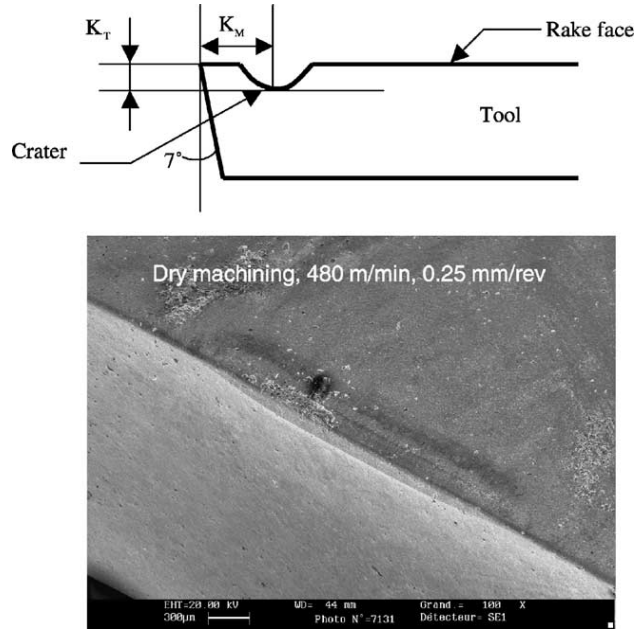

Figure 2: Crater Wear Measurement [2]

Tool condition monitoring systems have approached detection of tool wear over time from several perspectives: vibrational analysis, power consumption, acoustic emission and sound analysis. These methods can be categorized as *direct* method monitoring, or *indirect* monitoring. Direct monitoring systems evaluate the tool surface directly using image analysis and other means. Indirect methods evaluate tool wear by monitoring attributes that are closely correlated to wear. These indirect methods consist of cutting force, power monitoring, vibration, thermal properties, acoustic emission and sound emission. Indirect methods have the greatest potential to be adopted by industry because they generally do not require the process to stop, i.e. they can be monitored *on-line*. These indirect methods can be further classified as *proximal* or *remote*. Proximal monitoring systems require a sensor such as an accelerometer, thermal sensor or dynamometer to be placed in the immediate vicinity of the cutting process in order to achieve acceptable results. Remote monitoring systems can collect relevant data at a distance from the cutting process. Transmitted sound and power monitoring may both be classified as remote monitoring systems, whereas acoustic emission, thermal, vibration and cutting force monitoring are proximal. Remote monitoring methods would be preferable in actual industrial applications because they allow sensors to operate from protected areas and do not hinder motion or reconfiguration of work. Another important consideration is the increasing presence of micro-machining processes in industry. Micro-machining requires tight tolerances that are sensitive to tool wear and have very small cutting tools. Proximal sensing systems are difficult if not impossible to mount in the micro-machining environment, resulting in renewed interest in the development of remote sensing systems such as transmitted sound. This paper provides a much needed review of the methods involving transmitted sound analysis relative to tool wear monitoring and identifies the essential technical areas for further research.

2. Acoustic Monitoring Methods

Before proceeding with the review of transmitted sound methods, it is important to distinguish it from acoustic emission monitoring. Although tool wear monitoring using acoustics was based on machinists’ abilities to hear changes in machining conditions, most research over the last 50 years has focused on vibro-acoustic methods. One of the most well-researched monitoring methods is acoustic emissions (AE).

Acoustic emission as a physical phenomenon was documented by Kaiser in 1953 in his doctoral thesis [4], and is the measurement of sound propagated through the solid metal structure of the cutting equipment and/or work piece. Acoustic emissions are generated by elastic waves inside a metal body generated as a result of dislocations in the material. For cutting operations, this may be the result of microcracks at the in the material, friction rubbing, or the motion and interaction of surface asperities between the tool and the material, and/or microchipping of the tool surface [5, 6]. Tool degradation is monitored as a function of changes in the high-frequency stress waves occurring on the surface of the machined material. There has been a tremendous amount of research involving the use of acoustic emissions in conjunction with a variety of post-process techniques [6-9].

Acoustic emissions methods are capable of very high sensitivity and accuracy in identifying tool conditions, but have a number of limitations. The AE signals themselves are typically very high frequency with low amplitude and have a broad frequency range (100kHz to 2MHz). The high-frequency low-amplitude combination results in quick attenuation of the signal as the distance between the sound source and the sensor increases. In addition, as the distance between the source and the sensor increases, so does the opportunity for reflection of the signals from the inner surfaces of the mount structure and the introduction of noise elements to the data [4, 10, 11]. The sensor is often placed either on the tool holder or at the interface between the cutting tool insert and the tool holder. Recent investigations have been made into the use of coolant fluid as a transmitter for AE signals to allow a more remote location of the sensor. Unfortunately this method has its own problems, particularly bubbles and chips in the coolant stream [12]. The second but more easily surmountable limitation of acoustic emissions monitoring is the broad frequency band which provides an enormous amount of data. This is a double-edged sword as the wide range allows for flexibility in the types of operations and conditions that can be monitored using AE, but also requires tremendous computing power to complete the signal processing. Typically AE analysis is conducted by extracting a narrow frequency band of data from the range once the area of interest has been identified [10].

The need to have the sensor close to the work piece results in the risk of damage to the sensor in the industrial environment and is one of the major challenges to getting tool monitoring systems implemented in commercial shop environments [13]. High-precision machining operations have used AE sensors effectively when mounted directly to the work-piece [6], but the effect on the process cycle time due to sensor installation could make this type of monitoring process infeasible for high-volume production. With the advent of micro-machining processes, finding the space to install these sensors is becoming difficult as well [14].

Transmitted sound is generated by the same sources as those creating acoustic emissions, in conjunction with airborne noise from the surrounding environment. This audible sound is typically considered as from 50Hz to 20kHz and is measured using microphones. The primary value of using transmitted sound for monitoring is its ability to be used remotely. This remote sensing method may make it feasible for TCMS to be used outside of the laboratory, in harsh industrial environments and in the tight spaces of micro-machining operations.

3. Transmitted Sound and Tool Condition Monitoring

Audible sound has long been used by experienced machine operators to routinely distinguish table movements, tool types and tool conditions [15, 16]. Early machinists developed an ear for the conditions of their machines, but the first scientific evaluation of transmitted sound as a diagnostic tool was done by the General Electric Research and Development Center in Schenectady, New York during the mid-1960s. Research pioneered by Bjorn Weichbrodt called “mechanical signature analysis” moved audible sound diagnostics from an art to a science [17]. Weichbrodt found that the energy of the high-frequency portion of the sound emitted by a cutting tool increased significantly with wear. From that initial work, research into the use of transmitted sound as a measurement of tool wear has been developing slowly. The primary concern with using microphone measurements has been the extraction of the useful cutting operation signal from background noise. This challenge has been addressed through sensing systems, signal processing and intelligent decision systems.

3.1 Sensing systems

The predominant method used to measure transmitted sound in tool wear monitoring research has been the single microphone [11, 14, 18-23]. A single microphone cannot detect the direction of the sound it receives, although some directional preference can be given to signals based on microphone design. A single microphone will take in sound from the entire environment, other machines processes and people’s voices, as well as the reflections of sounds. Placement of a single microphone is also important. If it is placed too close to the sound source, near-field effects

will generate noise in the signal. Most research of transmitted sound applications identifies background noise as a problem, but few have developed successful processing methods to address extraction of useful cutting tool sound data. Studies continue to be done in laboratories where ambient noise levels are low compared to an active manufacturing environment. Recent exploration into alternative sensing strategies may provide some answers to the data extraction problem. These newer strategies are array-based systems and sensor fusion.

3.1.1 Array-based systems

Array-based systems use multiple microphones to generate an image of the sounds experienced in an area and have become more widely used as computing power has increased in the last five years. There are two basic approaches to using microphone arrays to measure sound contributions in an area based on the proximity of the microphones to the sound source. Both approaches yield an image of the sound generated which may be overlaid onto a two-dimensional photograph or three-dimensional computer model of the area. Array systems provide the unique ability to not only measure sound contributions, but to locate the sound sources in space. This enables an effective tool for removing background noise from the signal by focusing only on the data emanating from the source of interest.

Near-field, or acoustic holography, systems require a blanketing grid of microphones to be placed in close proximity to the sound source [24, 25]. They have been used extensively in the area of leak detection, and have only recently been investigated as a method for measuring tool wear sound. Original work with acoustic holography was on sources with very simple geometries, once the methodology was developed, conformal arrays have been used for measuring more complex surface emitters. Acoustic holography is done in the near-field in order to capture the evanescent waves radiated from the surface of the emitting surface. Thus the array must be positioned very close to the emitting machining operation to have good resolution [26]. The spacing of the microphones on the grid is also important as the distance between microphones must be less than the wavelength of the sound to be mapped. Thus high-frequency sounds will require a more densely populated (expensive) microphone grid [26]. The need for close proximity of the array to the machining operations defeats the primary advantage of using a transmitted sound system and it not feasible for industrial TCMS applications.

One of the only research works demonstrating the use of near-field holography to tool wear was that of Xue et al.. Xue used a 29-microphone array inside a hemi-anechoic chamber to map the sound emitted from a motor and a loudspeaker in two dimensions. Since his array was a planar design, and the machine surfaces emitting sound were complex in shape, Xue proposed the use of a combined wave superposition method to reconstruct the acoustic image based on the hybrid near-field reconstruction methods of Wu [27]. Xue's placement of the array at a distance of 1.5 meters from the emitting sources did not allow the evanescent wave data necessary to near-field holography to be captured. In addition, the array used was not a grid, but two linear arrays in a cross-planar orientation. This design created error in the phase and amplitude of the sound pressures on the holographic plane according to Xue [28]. Even with the problems in the construction of the experimental set-up, Xue was able to produce an acoustic map that clearly showed the two distinct sources in two-dimensions. Using blind source separation, he was able to extract the motor sound power spectrum data from that of the loudspeaker using the mapped amplitude traces.

Far-field, or beamforming, systems use relatively small arrays (in size and number of microphones) to capture data from a large surface or inside an enclosure. These arrays have been used in architectural [29] and automotive acoustic research [30] and are just beginning to be considered for TCMS systems. Generally, a beamformer assumes that sound is emitted from a surface that can be modeled as a collection of monopole sound emitters. The array must be positioned at some distance from the sound source as the evanescent waves can generate noise in the results. The distance from the each monopole source point to each microphone in the array can be described by a specific time delay based on the speed of sound in air. Using this information, sound traces can be generated for each monopole source in either the time-domain or the frequency domain. The results are typically provided as an acoustic image map of sound contributions received from sources in the area. Since beamformers based their measurement of the speed of sound propagation in a straight line, they are line of sight devices and cannot see sound hidden behind acoustically absorptive structures. Likewise, reflected sound impinging on the array will be treated as direct sound creating aliasing and ghosts in the acoustic images. By overlaying the acoustic image over a photograph or computer model of the source, these ghost images may be negated in the interpretation of the data. More detailed information on the signal processing associated with beamformers may be found in several excellent papers [31-33].

Recent work by Huang and Lu demonstrates the use of a 3-microphone beamforming system in the evaluation of a micro-milling process in the presence of noise [34]. They describe the array as linear in design set 50mm from the cutting source, 60mm apart, and vertically at the same level. A time-domain delay and sum method to reconstruct sound contribution emanating from the *x,y,z* location of the cutting point as a power spectral density function. There were not acoustic images generated. The beamformer results were presented in both filtered and unfiltered form and compared to the filtered results of a single microphone. The study concluded that the beamformer successfully extracts the original signal from the noisy environment and that the noise effects are further reduced by using a Wiener filter on the beamformer data. The experimental set-up here has the microphones unnecessarily close to the cutting source and should provide similar results at a greater distance based on the operating principles of the beamformer.

Recent array-based research has focused on the extraction of useful data from transmitted sound containing noise. While the near-field holographic systems may have limited use in industry, beamforming has the potential for use in a remote sensing TCMS. Once data for a specific location has been isolated, it may be processed like any other single microphone data to establish a correlation with tool wear. Further work is needed to show the full capability beamforming as a sensor in a noisy industrial environment and to make better use of the resulting image data.

Sensor fusion is the focus of the many recent research papers and involves the use of a variety of sensor types to characterize a condition. In the field of transmitted sound analysis there are two recent studies of note. Salgado and Alonso use two separate remote sensing systems, transmitted sound and equipment power consumption, to characterize the wear of a lathe operation tool,. A least squares version of support vector machines was used to estimate tool condition based on an estimated cutting force and the single spectrum analysis of the transmitted sound [11]. Ghosh et al. take sensor fusion further by considering four separate input signals: cutting force, vibration, spindle current and transmitted sound. Their analysis found that while cutting force combined with spindle current gave the best predictor of tool wear, sound pressure level and spindle current provide satisfactory results that were less intrusive and costly [35]. Sensor fusion requires complex high-level processing to give meaningful results.

3.2 Signal Processing Methods

Once the transmitted sound data has been collected as an analog microphone signal, the method of processing determines the performance of the wear monitoring system. Ultimately, the performance of any monitoring system must be measured by the degree of correlation between the data features selected as a model for the condition, and the condition itself. Figure 3 shows a block diagram of the signal processing steps required for a TCMS based on transmitted sound.

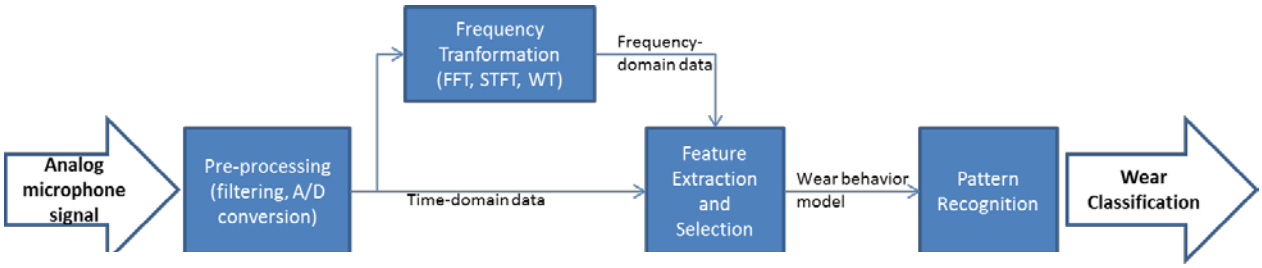

Figure 3: Processing of transmitted sound data

The analog microphone data is first pre-processed to make it suitable for use in analysis. This may include amplification of the signal, filtering, or segmentation, and finally an A/D conversion. The result is a set of digitized time-domain data. Filter methods are often used to reduce the effect of background noise; the assumption is that the cutting tool data is at a different frequency from the background. Digitized time-domain data is rarely used directly as a basis for modeling tool wear. Frequency domain data resulting from fast Fourier transforms (FFT), short-time Fourier transforms (STFT), or wavelet transforms (WT) are most commonly used. The early work of Weichbrodt et al. demonstrated a clear relationship between the amplitude of sound in a specific frequency band and wear which has be confirmed in a number of subsequent studies.

In 1987, Sadat and Raman found that tool flank wear created a rubbing noise at between 2.75 and 3.5kHz which increased from 9dB to 24dB as the sharp tool became worn on the flank. The increase in sound level was largest at the beginning of the wear and reached a saturation point as the flank wear progressed. Sadat and Raman were careful to explain that their results were achieved without any cratering in evidence [22]. In related work, Takata used a short-time spectrum analysis to develop signature patterns associated with 18 different operational sounds of a vertical milling machine. The operating sound data was partitioned into discrete time periods; and each was expressed in terms of a frequency spectrum pattern. Using methods similar to that of isolated-word speech recognition, Takata compared the sound patterns emitted from the machine to a set of standard patterns to identify the type of operation being performed. Although the method was generally successful in determining the correct active operation, Takata concluded that it was not reliable enough for real field use [16]. In 1991, Trabelski and Kannatey-Asibu found that as a tool wears, the lower frequency spectra (around 4kHz) increase significantly in power while the higher level spectra (around 6kHz) are diminished. Another important finding was that the frequency signature of a broken tool is very close to that of a sharp tool [23]. Delio and Tlusty used spectral patterns to identify instances of chatter in milling operations. In their work, the machine dominant frequencies were mapped based on the spindle speed and the number of flutes on the tool. Chatter was detected when a spectral frequency developed that could not be identified as a harmonic of the expected frequency of the machine. These chatter frequencies varied based on the spindle speed of the machine and the depth of cut [36]. In the field of micro-machining, Chen et al. found peak sound spectral energy shifted to higher frequency levels with tool wear, whereas the vibration data taken did not show this effect. This served to emphasize the value of transmitted sound as a monitoring method for micro-tool wear. More recently, Bagci used spectral data to evaluate cutting conditions of a surface milling machine. The complex combinations of cutting directions and deflection angles on the cutting tool as it traversed the sculptured surface were described in terms of sound pressure levels at frequency. Bagci found that there was a strong, positive linear relationship for both feed rate and cutting tool deflection relative to sound pressure level at specific frequencies (r=0.7) [18].

Time domain data has been used by Alfonso and Salgado and was processed using singular spectrum analysis to extract trends from transmitted sound data traces. This non-parametric technique describes time domain data as a set of eigenvalues for a trajectory matrix. The larger eigenvalues represent the low frequency region of the spectrum, whereas the high-frequency region is represented by the smaller eigenvalues. Hence this time domain method is really creating a frequency domain model.

3.3 Tool Wear Classification- Pattern Recognition

A typical pattern recognition system for a transmitted sound TCMS may be described in three steps: 1) sampling of the sound data, 2) signal-processing of the data and selection of the data features; and 3) classifying the feature data as a degree of wear. By the 1990s computer performance provided increased speed in spectral analysis computations and paved the way for more development of the methods to classify the degree of tool wear associated with transmitted sound data. At the University of Michigan, Trebelski and Kannatey-Asibu sought to develop a means to classify a tool as sharp, worn, or broken. They selected features from the spectral data as a combination of average amplitudes of sound power from defined frequency bands, and the overall sound power. Although a tool could be classified reliably as worn or sharp based on only two features (low frequency band 0- 5kHz, and high frequency band 5kHz to 10khz), to distinguish between a sharp and a broken tool was problematic as the frequency signatures were very similar. To achieve a reliable classification of a tool as sharp, worn or broken, at least five features were needed and the optimum performance was with nine features (eight frequency band assessments and the overall sound power). The actual classification of the sound data samples was done using least-squares minimum distance criteria. In this method a least squares discriminant is calculated which gives a probabilistic value for the data belonging in each classification. The classification with the highest value is the resulting decision.

For sensor fusion applications such as for Ghosh et al., an artificial neural network (ANN) approach provided the ability to combine feature data from different sources with different level of correlation and non-linear responses. As with any decision system, the result can only be as good as the data presented to it. Hence a significant amount of thought must be put into the selection of the features to be used. Ghosh et al. use a cross-correlation chart to evaluate and select the features that will be used in their feed-forward ANN. The results of their study was that the fusion of spindle motor power data with cutting force data gave the best prediction of the magnitude of *Vb* (error of 23μm for filtered data). They take care to note however that direct measurement of cutting force in industry would be difficult;

thus they recommend a fusion of spindle motor current and sound pressure level (error of 50μm using filtered data) as most feasible.

Salgado and Alonso use a least-squares support vector machine (LS-SVM) to estimate the amount of tool wear (*Vb*) based on the combined features of the four eigenvalues resulting from a singular spectrum analysis of the transmitted sound, feed motor current data, and the cutting conditions of speed, feed and depth of cut. They found that the prediction accuracy increased significantly at higher cutting speed and feed rates due to the better correlation with cutting forces. Interestingly, Salgado and Alfonso compare the results of their LS-SVM based transfer function and that derived from an (8-7-1) ANN. They found that the accuracy was similar between the two methods when large training data sets were used (both had RMS error around 6.8μm), but the neural network approach was more sensitive to the size of the training data set (RMS error 19.15μm) relative to the LS-VMS method (RMS error 17.05μm).

4. Conclusion

Transmitted sound has demonstrated its feasibility as a tool condition monitoring method first as a qualitative assessment for conventional machining operations done by machinists, and has evolved into an increasingly active area of research. Originally eschewed for the significant amount of background noise collected along with the data, transmitted sound has spurred renewed interest with the advent of micro-machine processes in industry.

Micro-machining operations typically require the use of more fragile tools and have more costly results when tolerances are not maintained. Research into transmitted sound monitoring of micro-machining processes has been the focus of many recent TCMS publications. This is because micro-machining processes do not have enough space available in the immediate vicinity of the cutting operation for acoustic emissions sensors or dynamometers to measure cutting force. Conventional machining operations may also benefit from remote sensing systems such as transmitted sound. It is conceivable that sensors mounted on or near cutting operations may become a regular expense as they are damaged in the rough industrial environment of the machine shop. The initial cost of installing a monitoring system based on proximal sensors would also be large, as each individual cutting operation would require its own instrumentation. Manufacturers that are agile and adjust their shop layouts to the product would find the wiring for the monitoring systems to be an encumbrance. Remote sensing systems provide the ability to disconnect the sensor from the machine itself. Technology such as beamforming using microphone arrays has the potential to provide monitoring of several machines concurrently from a remote location while reducing the amount of background noise in the data.

A number of challenges persist in developing industrial TCMS applications using transmitted sound. Background noise suppression and feature extraction continue to be a challenge and require more research to make reliable systems capable of working in these harsh environments. More research needs to be conducted in actual industrial environments to show their feasibility. The effect of fluid cooling systems, commonly used in industrial machining, could have significant effects of the analysis of transmitted sound if the frequencies overlap those of the cutting operations. Tool wear due to cratering has not been adequately addressed in current research and is a significant contributor to the decision to change a tool. To make these systems more cost-effective, more research is needed into the potential of beamforming technology to enable central monitoring of several systems. In addition, sensor fusion has demonstrated an ability to improve the prediction accuracy for tool wear, but the number and type of sensors must be optimized based on life cost analysis.

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