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Acoustic and vibration monitoring for the avoidance of catastrophic tool failure in Manufacturing

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Abstract:* There has been considerable research from both an academic and industrial perspective into the monitoring and control of CNC machining processes. This work has been continued by the consortium engaged in the REALISM project, an EU-FP7 funded project which is investigating the use of sensor fusion in a real time production environment, to monitor CNC tool wear and catastrophic tool failure (CTF) through the use of three sensor technologies - Force, Acoustic Emission and Vibration. Tool failure may cause substantial damage to the tool, the work piece and/or the machine tool. Detection of tool tear and CTF (chipping and breakage of the cutting tool) plays an important role in improving reliability and promoting automation of manufacturing processes. The occurrence of consistent anomalous sensor signal features (SF) was identified prior to catastrophic tool failure during single point turning tests of high carbon tool steel. A number of characteristic features have been identified to allow for an early warning system for the prevention of catastrophic tool failure.

Keywords: **Acoustic monitoring, Vibration Monitoring, Tool Condition Monitoring, Catastrophic Tool Failure, CNC Machining, Sensor Fusion.**

I. INTRODUCTION

There has been considerable interest, for both scientific and commercial reasons, in the potential to apply automation and intelligent monitoring to manufacturing operations for a number of years. One of the fundamental manufacturing operations that have been investigated from a process monitoring perspective is machining, which is the subtractive manufacturing process whereby a computer controlled machine is employed for the removal of material from a raw material to result in the creation of a product. Even with the use of sophisticated computer numeric controls (CNC) in recent years, this manufacturing process continues to be heavily dependent on a high level of operator skill to ensure the acceptability of the resultant product. It can be readily identified from a search of the literature that there have been a large number of investigative projects undertaken, many on an industrial-academic-governmental basis such as that undertaken by Allied Signal and the US defence department [1]. A closer look at more recent projects that have been undertaken within the EU FP7 collaborative funding programme, such as ADACOM [2], IFACOM [3], SOMMACT [4] and REALISM [5] further serves to illustrate the desire that exists to scientifically control the CNC machining process.

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In fact, such has been the extent of research into the possible methods that may be employed in the monitoring of the CNC machining process through recent decades it has been possible for a number of comprehensive state of the art reviews to be undertaken to allow a snapshot of the current level of progress. One of the earlier milestones was laid by Tlusty [6] serving to capture the state of the art from work that had been undertaken up to that point by research such as that undertaken by Micheletti [7]. A further state of the art review was published by Tonshoff [8] and there was sufficient work undertaken through the intervening years to allow Byrne [9] provide an updated state of the art. The most recent state of the art review available is by Teti *et al* [10] and this provides an overview of all the investigative avenues that are being pursued in the area at this point.

Early work into the area of monitoring of the CNC cutting process focussed on a number of physical emissions from the process, including audible sound energy, acoustic emissions, cutting force, vision detection, motor currents, vibration and temperature.

Each of the physical emissions detailed above have been proven through the research to have some worthwhile information that could potentially be used in the detection of both tool wear, and catastrophic tool failure. Cutting force was investigated by Cuppini [11], Acoustic emission was evaluated by both Dornfeld and Pathak [12,13], vision systems were outlined and investigated by Kurada & Bradley [14,15], there have been a number of investigation as to the worth of temperature [16–19], and likewise there have been numerous studies on the effect of vibration [20–21] and audible sound energy has been demonstrated by the co-authors of this paper [24]. Further to the analysis of individual physical emissions from the process, more recent work has tended to focus on the analysis of sensor data from multiple sensors [25].

Through the research it has become evident that the analysis and interrogation of the data from the physical emissions in the machining process is now just as important as the actual sensor data. A number of methods have been employed for the interrogation of this information such as Neural networks [25–27], wavelet analysis [28], hierarchical integration [29] and sensor fusion [30] for example.

The participants in the REALISM project choose the most valuable process emissions to be analyzed based on their research. These emissions include; Acoustic Emission (AE_{rms}), Vibration (V_x, V_y & V_z) & Force (F_z, F_y & F_x). The

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analysis of the obtained results presented in this paper is a follow on from the initial presentation of the results at the CIRP CMS 2015 conference.

A. Overview of the REALISM Project

The work that is being presented in this paper has been undertaken as part of the REALISM project, which is an FP7 funded research project with participants across a number of member states within the European community. The aim of the project is to develop a system which provides real time information on the status of the CNC machining system through sensor fusion and intelligent data analysis.

B. Sensor System Deployment

It was agreed that the sensors to be deployed on CNC machine tools for the investigation would include an AE sensor, a vibration sensor and a force sensor (Figure 1).

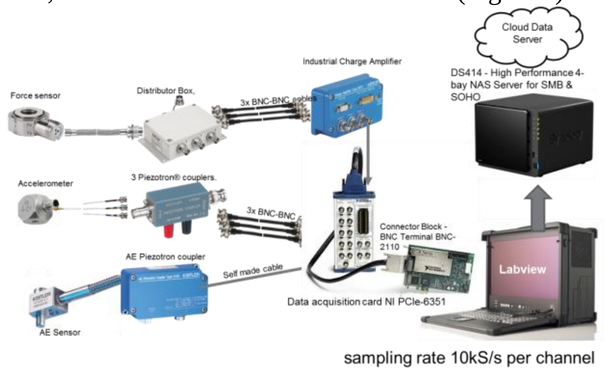

Fig 1. The REALISM sensor configuration

The sensors are deployed on a 3-axis CNC lathe (Mazak Quickturn Nexus 200II) with cutting tests to focus on turning operations.

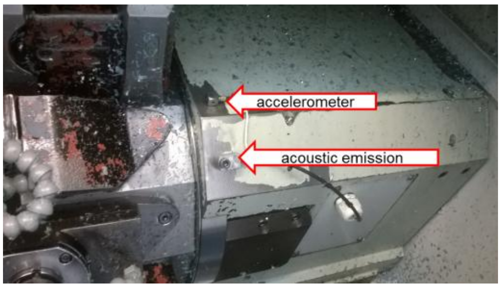

Fig 2. Position of installation sites of AE & Vibration sensors

Fig 3. Location of force sensor in drilled pocket

The AE sensor and the accelerometer are installed on the machine turret, as illustrated in Figure 2. Due to operational restrictions the force sensor could not be installed at the interface of the turret and the main machine body as originally envisaged. A number of locations were identified through which forces would likely be transmitted- thus it was decided to position the force sensor into the structure of the machine, by drilling a hole into the sliding head (Figure 3).

C. M-code and G-code Programming

For effective signal data analysis, it was imperative to distinguish between machine operation (tool changes, turret movements, coolant on/off) and machine cutting (cutting feed). To achieve this, the CNC controller had to be given additional functionality with the expansion of machine codes (M-codes). The additional M-codes allowed the machine programmer to implement G-code programming to switch on/off analogue relays and digital signals (logic 0 or 1) to control data acquisition parameters.

D. Application of Neural Networks in Tool Wear Monitoring

A neural network approach is being used to analysis the results of the sensor data. This analysis will correlate signal features to the degree of tool wear as a means of future wear predication. The neural network approach has recently been the most intensively studied method for feature fusion [31–34]. Usually, a single neural network is used, where several SFs are fed into the network inputs, while the tool wear estimation is the network output. In some works, however, hierarchical tool wear monitoring strategies were proposed. The system presented in reference [35] employs several measures of the cutting force, acoustic emission, and vibration. It consists of two modules where the first one estimates the tool wear from all SFs taken from one sensor and the cutting parameters. A single radial basis function artificial neural network was used there. The results obtained in the first module were integrated into the final system's response in the second module, in which a fuzzy neural network was used.

E. Validation of the monitoring process

A further objective of the REALISM project is to validate the resultant system to confirm that decisions are correctly made. The baseline standard ISO 9001 states that "The organization shall validate any processes for production and service provision, where the resulting output cannot be verified by subsequent monitoring or measurement".

Verification can be thought of as a method of testing that provides assurance at a point in time that a product will do what it is intended to do without causing another problem. Validation on the other hand provides measurable evidence that over time the product will work properly. In the medical devices industry, process validation is generally seen as the endpoint of all validation activities, as illustrated in Figure 4.

In applying validation to the REALISM project, several aspects are taken into account. The TCM consists of a 3-axis force sensor, an acoustic emission (AE) sensor, a 3-axis accelerometer, a data acquisition system, an industrial portable computer, custom data logging software and custom control software linked back to a HMI. While systems may be rule or knowledge based in their decision making, here the control software incorporates a neural

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network Case-Based Reasoning (CaBR) system, which requires the operator to initially teach the TCM by identifying when a pre-determined number of tools are worn. From this teaching, the TCM will compare the learned results against process conditions, gathered from the sensors, allowing the system to make decisions around the degree of tool wear present on the cutting tool. Gonzales [31] proposes that "Validation of knowledge-based system has received great attention from researchers in the last several years", that "however, the majority of the reported validation work to date has centred on rule-based systems" and that "published literature that deals with validation of Case-Based Reasoning (CaBR) systems is indeed scarce". This will present challenges from a TCM validation perspective.

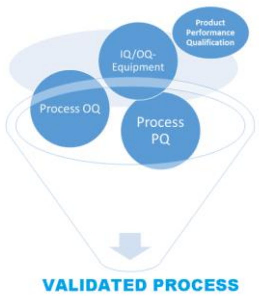

Fig 4. Process validation illustration

Validation of the CaBR system shall establish whether an individual test case has been solved correctly through benchmarking against learned information acquired from operator expectation. Gonzales *et al* suggest that this consists of determining two basic parameters, the Result Acceptability Criteria (RAC), and the System Validity Criteria (SVC). The RAC serves to determine whether an individual test case has been solved correctly by the CaBR system. It is the distance between the system solution and the benchmark standard that are then measured. Further work will be undertaken on the validation of the data presented in the experimental results below.

II. EXPERIMENTAL RESULTS

Single-point turning operations were completed on high carbon tool steel. Data was recorded using a sample rate of 10 kHz. The cutting inserts were machined to catastrophic tool failure (CTF) an example of which can be seen in Figure 5.

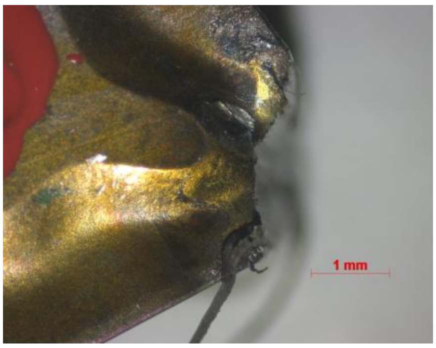

Fig 5. Example of insert catastrophic tool failure

Figures 6 & 7 show the sensor signals detected in the lead up to the occurrence of CTF in two cutting operations. The broken line (cutting feed) is a digital signal acquired showing when cutting (1) and no cutting (0) took place.

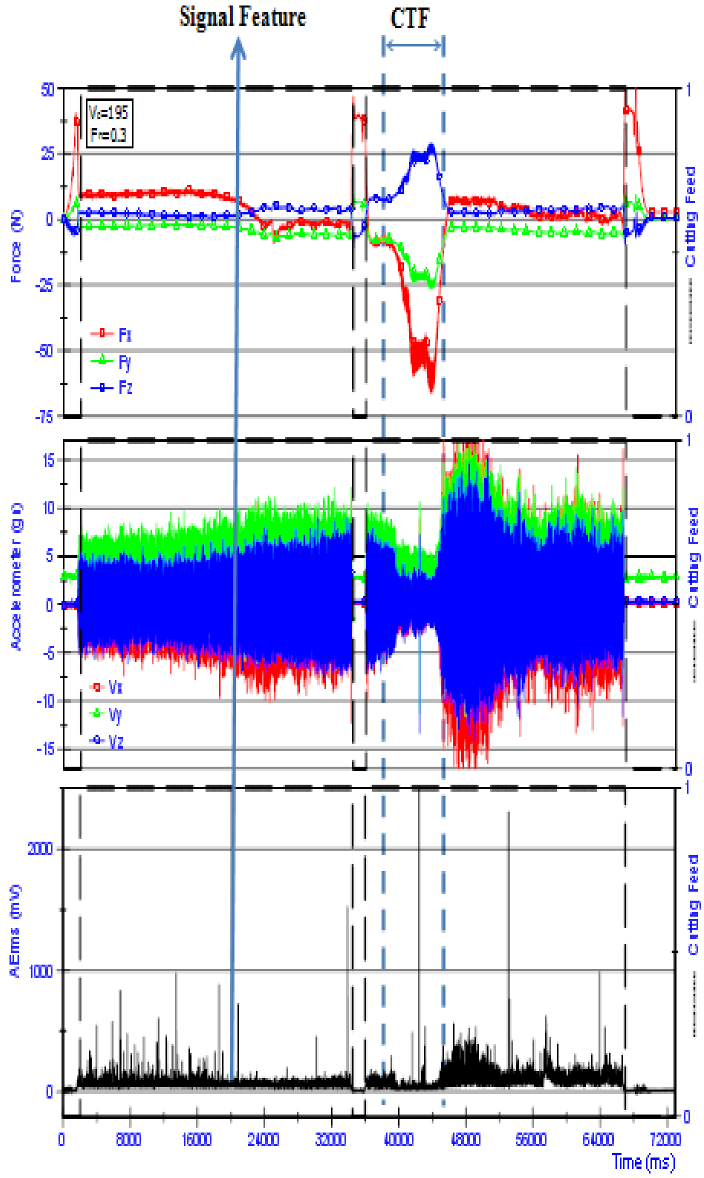

Fig 6. Operation1. Sensor signals during the occurrence of CTF.

Figure 6 shows two cutting passes with CTF occurring early on in the second pass. Figure 7 shows two cutting passes with CTF occurring towards the end of the operation on the second pass. In both operations, there are consistent anomalous signal features (SF) indicated by the "SF" band in advance of the CTF event indicated as "CTF". Signal feature characterization was completed at the "SF" band (approx. 2000ms) to determine suitable characteristic features that could be used to indicate the imminence of catastrophic tool failure.

Figures 8 and 9 shows that the resultant accelerometer (Vt (RMS)) and force data (Ft(N)) change in relation to tool wear (Vb), signal feature (SF) and maximum signal at Catastrophic tool failure (CFTmax).

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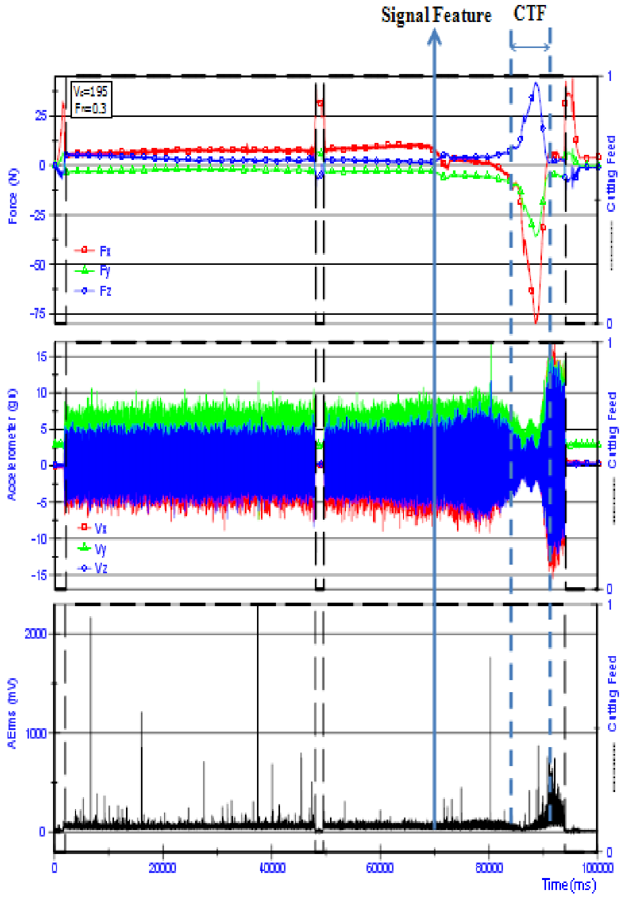

Fig 7. Operation 2.Sensor signals during the occurrence of CTF.

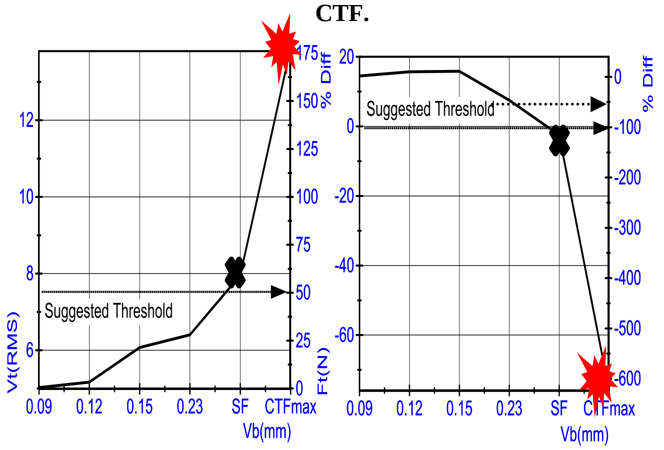

Fig 8. Operation1. Resultant accelerometer and force data in relation to tool wear, SF and CTFmax.

A rectangular windowed FFT was carried out on the Vx component. The window duration was quite long at 2000ms in order to a build-up in the frequency bins of repeating signal components, thereby dominating the intermittent signal components. This analysis was performed for Operation 1. Figure 10 shows the FFT, on the left, and, on the right, homes in on the centre third octave frequency amplitude in relation to gradual build-up in tool wear, represented by increasing energy in this frequency range to the point of the SF.

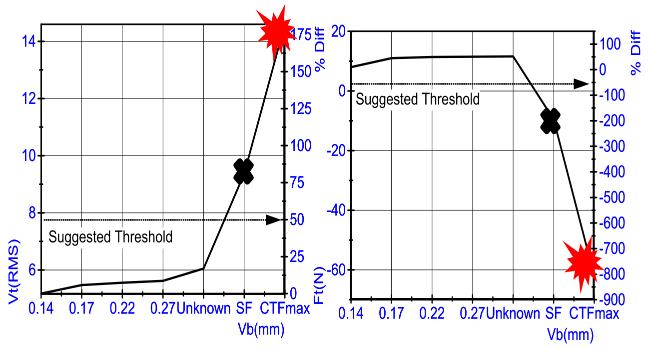

Fig 9. Operation 2. Resultant accelerometer and force data in relation to tool wear, SF and CTFmax

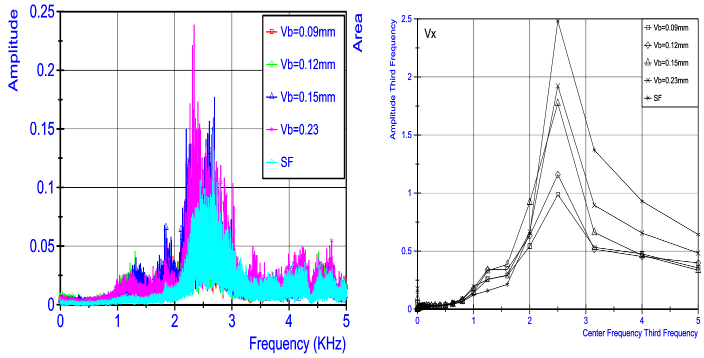

Fig 10. Centre third octave frequency amplitude.

Surface roughness measurements were completed using white light interferometry to ascertain if work piece surface roughness was within acceptable tolerances (Figure 11).

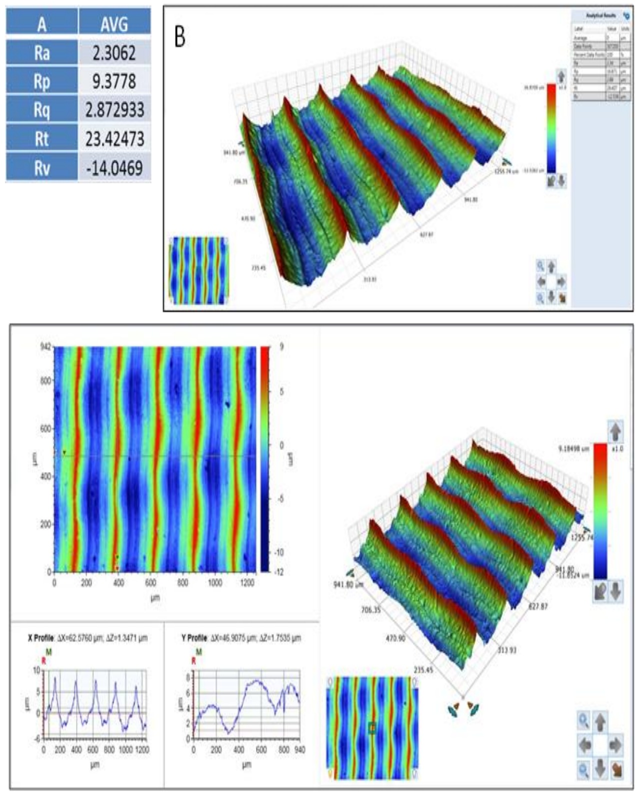

Fig11. Work piece surface roughness measured by white light interferometry.

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Optical microscopy was utilised for tool wear measurement and to analyse too failure mechanisms (Figure 12).

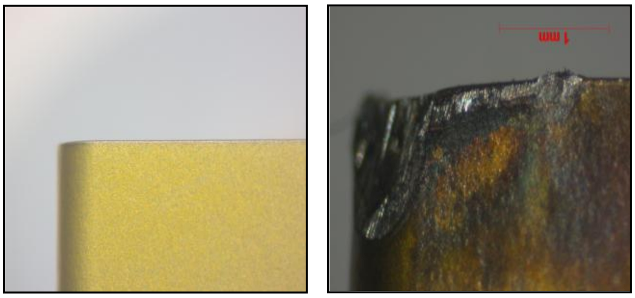

Fig 12. Optical microscope pictures showing an the flank side of an unworn cutting tip (a) and tip exhibiting significant notch wear (b).

III.DISCUSSION

The machining of hard wearing metals may result in pronounced in-process tool wear and CTF. Ideally tool wear should be monitored by stopping the process intermittingly and completing a visual inspection of the tip, but this is not always possible in areal time production facility. Experienced CNC operators may use "tell-tale" signs of enhanced tool wear including; visual analysis of the cutting chip, changes in sound, the monitoring of motor power consumption, but inexperienced operators may not always recognise these. Enhanced tool wear and breakages often affect the work piece surface beyond recovery resulting in its discard and machine downtime. A multiple sensor system was deployed on a CNC lathe during turning operations and a signal assessment was completed.

A number of indicative anomalous signal features (SF) were observed prior to in process catastrophic tool failure. Microscopy observations of the insert during cutting suggest that these signal features are a result of insert failure mechanisms, initially by tip failure as a result of significant notch wear (Figure 12) followed by complete tool breakage (Figure 5). Effective characterisation and identification of these signal features and there implementation in a tool condition monitoring system could ensure corrective actions, thus preventing the occurrence of catastrophic tool failure.

Figures 8 and 9 show that the resultant accelerometer and force data changes with increasing tool wear. Taking the first reading as a reference point (i.e. "good" reading with unworn tip), the % Diff axis shows the percentage difference between each data set and the reference point. CFTmax shows the maximum recorded value during tool failure. Figures 8 and 9 show that measured Vt (RMS) at the SF was 62% and 80% greater than the reference point respectfully. Ft(N) were -117% and -190% at SF in relation to the reference point. Work piece surface roughness measurements were completed during the cutting operation to determine effects of tool wear. At circa 50% (%Diff) for Vt(rns) and -50% (%Diff) for Ft(N), the surface roughness values (R_a) were within tolerance. This suggests that setting a machine threshold at these values ensures acceptable surface finish.

FFT analysis of the Vx component of the accelerometer data (Figure 10) shows that over a 2000ms time frame, the centre third octave frequency amplitude increased with tool wear and SF suggesting that this is an effective way of identifying tool wear and the onset of CTF.

IV. CONCLUSION

A number of challenges were successfully over come in the deployment of three sensors for the tool condition and process monitoring of a real time production CNC machine. The occurrence of a consistent anomalous signal features (SF) was identified prior to catastrophic tool failure during single point turning tests of high carbon tool steel. A number of signal characterization techniques have been identified to allow for tool wear prediction and an early warning system for the prevention of catastrophic tool failure. The prevention of such events will play an important role in improving reliability and promoting automation of subtractive manufacturing processes.

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