CNC Spindle Signal Investigation for the Prediction of Cutting Tool Health

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Abstract

The deterioration of cutting tools plays a significant role in the progression of subtractive manufacturing and substantially affects the quality of machined parts. Recognising this most organisations have implemented conventional methods for tool management. These reduce the economic loss associated with time-dependent and stochastic tool wear, and limit the damage arising from tools at end-of-life. However, significant costs still remain to be addressed and more development towards tool and process prognostics is desirable. In response, this work investigates process deterioration through the acquisition and processing of selected machine signals. This utilises the internal processor of a CNC Vertical Machining Centre and considers the possible applications of such an approach for the prediction of tool and process health. This paper considers the prediction of tool and process condition with a discussion of the assumptions, benefits, and limitations of such approaches. Furthermore, the efficacy of the approach is tested using the correlation between an offline measurement of part accuracy and an active measure of process variation.

1. Introduction

It is known that cutting tool wear associated with metal removal contributes to a change in product form and hence a reduction in process accuracy and quality. Product form has been the motivation for a number of studies into quantifying the role that cutting tools play in process accuracy, and in determining the deterioration of cutting tool condition (Ahmed et al., 2016, 2017; Li et al., 2014; Liu et al., 2010; Zhang & Zhou, 2013). This is often through measurement of the product geometry. However, most of these neglect the significance that many industries place on product tolerance. A failure of a part to comply with the specification equates to economic losses for most organisations. To that end, there exists a growing number of in-process solutions available for re-dimensioning of cutting tools. These include in-cycle-gauging (ICG) approaches and programmed control solutions (including active process controls). These solutions hide the evidence of cutting tool wear and significantly hampers the possibility for post-process geometry measurement as an approach for tool condition monitoring (TCM).

2. Tool Condition Monitoring

Within the wider context, TCM is defined as both the direct or indirect acquisition and processing of system information before, during or after a process, and the subsequent analysis and classification thereof.

TCM is popular within academia and has subsequently been widely researched (Ambhore et al., 2015; Dongre et al., 2013; Liang et al., 2016; Prickett & Johns, 1999). However, despite the popularity within academia, TCM has not been adopted as successfully within industry. This could boil down to the stochastic element within the process, whereby the nature of the tools themselves and of the manufacturing processes introduce more influencing factors than is feasible to consider or account for (Engel et al., 2000). Alternatively, the cost vs benefits of such TCM systems confines them to academia. Promising in theory but impractical and expensive in context (Mitchell, 2007; Siddiqui, 2008; Wheeler et al., 2010). Ultimately, however (In the current state) TCM has not been able to translate from the controlled conditions of academic research to the relatively messy applications within industry. This indicates a need to bridge the gap.

From an industrial stance, and considering only the cutting tool, the typical approach by organisations is to act conservatively. Cutting tools are often assigned a finite working life, upwards of 20% less than the average working life, and often replaced at the discretion of the machine operator (Liu et al., 2015; Wiklund, 1998; Zhou & Xue, 2018). This safety factor minimises unplanned machine downtime and maximises the measure of machine availability. However, whilst providing marginal peace of mind, this approach does nothing to accommodate the risks present from stochastic wear and at best increases cost (Aliustaoglu et al., 2009; Zhou & Xue, 2018). It therefore seems obvious that to reduce process waste requires the implementation of appropriate TCM approaches, especially those that employ tool and process prognostics (Grosvenor & Prickett, 2011).

The manufacturing industry has moved towards smarter machines and a degree of condition based monitoring (CBM). Modern machining centres are often capable of actively monitoring their processes and adjusting to maintain speeds and/or feeds, or adjusting parameters to protect the machine from damage. This makes it common for modern vertical machining centres (VMCs) to be capable of identifying broken cutting tools or damaged spindles. Further innovation comes from the many involved industries towards the notion of 'smart factories' (Bosch Rexroth AG, 2015; MTConnect Institute, 2018; Siemens AG, 2018; Yamazaki Mazak, 2014). However, consensus on the necessary output or reaction from such systems is limited; many are content to provide the data with no liability for the process with the user being required to gather all the information possible in the hope that some will be useful. This indicates that efforts towards industry friendly solutions for active TCM and tool/process prognostics is desirable.

3. TOOL AND PROCESS PROGNOSTICS

In manufacturing, the theoretical potential, or 'added value' offered by the appropriate application of prognostics is apparent (Elattar et al., 2016; Jain & Lad, 2016; Rigamonti et al., 2016). In this context, it may be asserted that:

- Process efficiency can be improved through prediction of machine and/or tool failures. This allows for appropriate remedial action to be determined early and hence applied quickly (Improving the measure of machine availability).
- Risk can be reduced through detection and management of damaged or failing tools and equipment, hence reducing the occurrence of scrap products and limiting the effect of damaged tools on the process output.

However, it is also evident that despite the theoretical potential, the majority of practical prognostic approaches remain limited in capability (Engel et al., 2000; Gugulothu et al., 2017; Line & Clements, 2006; Wheeler et al., 2010). Prognostic methods often suffer from issues that limit their adoption and the confidence in their use, including:

False alarms - False alarms contribute to a reduction in effective useful life and come at a high cost to the process and the end-user both economically and in terms of confidence. Effort is required to reduce their impact for approaches to be accepted and successful (Bain & Orwig, 2000; Wheeler et al., 2010).

Prediction inaccuracy - Inaccurate predictions of tool and process health, or RUL, have the potential to result in unanticipated failures or for reductions in product quality to go unobserved. Many methods for prognostics claim high accuracy in use, however these claims are based on the enactment of given process conditions and often fail to translate from study to industry. The uncertainty this presents lowers the appeal of the given methods (Elattar et al., 2016; Line & Clements, 2006; Saxena et al., 2010).

Process limitations - Many approaches are proven for one process and assumed applicable to similar processes. The process-specific nature of a chosen method can be a determining factor in the acceptance of a system. If the system benefits cannot be accurately quantified the approach is unlikely to gain acceptance (Elattar et al., 2016; Saxena et al., 2010; Wheeler et al., 2010).

Nevertheless, depending on the process capability and/or the end-user requirements, the impact of the aforementioned issues can be reduced and in some cases neglected entirely. In these cases the potential process improvement offered by prognostics approaches is significant.

This work presents the existing spindle control signals from a typical VMC, with consideration of both the benefits and limitations of the approach. Additionally, the change in cutting tool condition is investigated through a comparison between the control signals and the variation in part geometry. This will enable the detection and management of tool and process conditions, without impacting on the process performance, whilst complementing existing methods for controlling dimensional performance. This will demonstrate that even simple methods can be suitable when high expectations of process capability and variation are not overindulged. This sits within the wider context of improving tool management techniques in order to provide a basis for more accurate, reliable and repeatable machine operations.

4. METHOD

This study employed a MAZAK Vertical Centre Smart 430A (VCS430A) VMC coupled with a MAZATROL Matrix Nexus 2 CNC Controller (NC). The VCS430A embodied a typical small scale VMC, commonly employed within the manufacturing industry by small and medium-sized enterprises (SMEs), whilst the NC embodied the typical intelligent control that seems popular in the current market.

In continuation of recent work undertaken at Cardiff University (Ahmed et al., 2016, 2017), a series of regular artifacts were manufactured using fully flooded cutting conditions. The artifacts were monitored in process to capture the CNC process signals and assessed post-process to identify the variation in product accuracy. The method involved the manufacture of eight cylindrical artifacts per series, followed by single-axis slots cut in two groups of four (Figure 1). Each artifact was composed of four identical sections, each henceforth considered as a manufactured part (I.e., 48 parts per series – Inc. slots). The process continued until either four series' (192 Parts) were completed or the cutting tool broke, whichever occurred sooner.

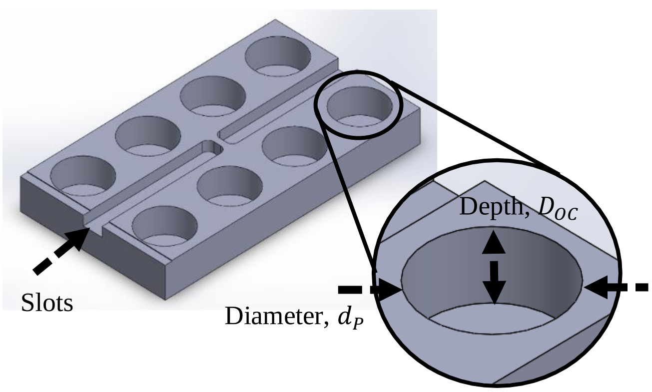

Figure 1. CAD Model Illustrating Artifact Design and Significant Geometries

The cutting tool used in this study was a 10mm, four-flute square-end-mill. The reasonably small size promoted a short lifecycle. In addition to the small size, the cutting tool was High Speed Steel (HSS), rather than carbide (Or similar), with no additional coating. The material information and process settings are identified in Table 1 and Table 2.

Table 1. Product Material Specification

Material	Dimensions	Type
Bright Mild Steel	125x25x220	Flat Bar

Table 2. Process Settings

	Value
Start Condition	Pre-Used
Cutting Speed (m/min)	52.0
Spindle Speed (rpm)	1646.0
Plunge Feed (mm/min)	111.8
Loop 1 Feed (mm/min)	223.6
Loop 2 Feed (mm/min)	279.5
Total Parts	128.0
Breakage	TRUE

4.1. Pre- and Post- Process Monitoring

The initial cutting tool dimensions were acquired pre-process using online (in-machine) measurement of the cutting tool using a physical contact tool-setter. The part dimensions were acquired post-process using a Coordinate Measuring Machine (CMM), with a Renishaw Revo1 retrofit, and interfaced through Renishaw's Modus software.

The significant product geometries were defined as the driving dimensions and hence used for the evaluation of part accuracy. This included the artifact depth and the manufactured part diameter. Only the fourth part in each artifact was considered due to the evidence of uneven tool wear, as also observed by Wilkinson et al. (1996) and Ahmed et al. (2016, 2017). The slots were measured for their surface finish, but otherwise considered insignificant.

To present the part accuracy in a suitable format illustrating the process variation and comparable with the spindle control signals the cross-sectional area (CSA_P), per unit depth, was calculated (Eq. (1)).

$$|\Delta CSA_P| = \left|\frac{\pi}{4}.\left({d_N}^2 - {d_P}^2\right)\right| + \Delta CSA_{P-1} \qquad (1)$$

Where the resulting area is the difference between the nominal diameter (d_N) and the actual diameter (d_P). The CSA was used to define the parts, rather than a measure of volume, as the actual depth of cut per part cannot be derived from the finished product.

4.2. In- Process Monitoring

The acquisition of the CNC process signals utilised the VMC PLC and an external PC, with the CNC process signals transferred via Ethernet protocols in 504 byte packets. These packets were transferred to the local memory of a Hilscher CifX50E-RE interface board (HIB) with a per-packet delay of 100ms, each being overwritten by the data within the following packet. Data was acquired from the local memory of the HIB through application of a simple C++ executable, created to monitor the VMC for activity, and initiate data acquisition during machining. This work considers only the acquisition of spindle motor load (SML) data. The process capability is summarised in Table 3.

Table 3. VCS430A -> PC Communication Capability

	Capability
Data Range (bytes)	0-504
Sampling Frequency (Hz)	64
Output	8-bit unsigned bytes

To enable a comparison between the SML change over time and the measure of part accuracy, the acquired data was converted from the original percentage load into energy consumed per part. To achieve this the signal was reverse-engineered using the spindle speed-power-torque (SPT) characteristic for the spindle motor (Figure 2).

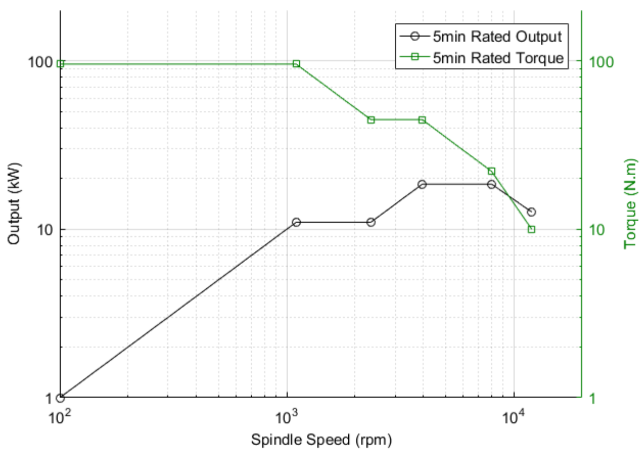

Figure 2. Spindle Motor Speed-Power-Torque Characteristic, Adapted from Yamazaki Mazak UK Ltd (2015)

This resulted in a curve illustrating the process energy required per part. To facilitate a comparison with the part geometry variation, any outliers were shifted to within the boundary of the overall trend through application of a Hampel filter. This achieved an approximation of the primary trend in the process variation. It is acknowledged that this method removes any variations due to differences in cutting speed, feed and depth, and that the probability this method hides stochastic elements of the process condition is high, however at this stage in this work this paper is primarily concerned with establishing a method that can be applied to the overall process condition. This will be extended later with the acquisition and analysis of more process signals using the installed system.

4.3. Part-Process Comparison and Remaining Tool Life

To quantify the part-process correlation and to identify the different stages in the tool condition, steps were taken to define the variation mathematically. This used polynomial approximations of the geometry and process signal variations. The initial approximations follow the general equation for a third order polynomial. The classification of these curves then followed a simple algorithm, summarised in the following steps:

1. The curve was shifted to zero at the stationary point. This was found to be more stable when using partial data sets, than shifting by the mean average of the data.
2. The data was split across zero with values normalised between zero and ±1 according to their sign. This emphasised the process change in the positive and negative gradients and separated the data into two parts, the new tool and the worn tool.
3. The magnitude change in the slope of the first differential was calculated, per part, from the general equation. The resulting maximum and minimum values were taken as the change between stages (herein referred to as the characteristic curve).

5. RESULTS

5.1. Part Accuracy

Initially, the variation in part geometry was established as the measure of process health (Figure 3).

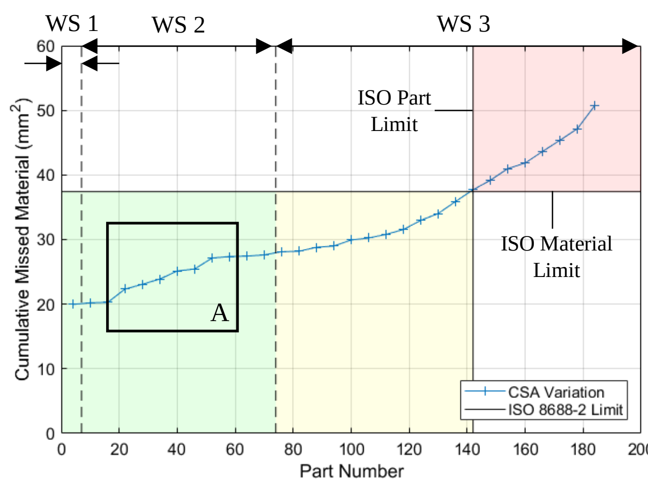

Figure 3. Estimated Stages of Tool Wear (GEO)

Characterising the variation in geometry is useful as the starting point for an in-process prediction of tool and/or process health. Colour is incorporated into Figure 3 to emphasise the different stages of tool wear. The green region (Parts 0-74) indicates the first two stages (WS 1 & WS 2), the rapid initial wear period and the subsequent period of gradual wear. The yellow and red regions (Parts 75-200) indicate the final stage (WS 3), the rapid wear to failure. The final wear stage is separated into two regions, one either side of the ISO 8688-2:1989 limit, identified as stages three and four. Table 4 indicates the stages of cutting tool wear, with an indication of their range (In parts) as estimated from the characteristic curve.

Table 4. Estimated Stages of Tool Wear (GEO)

Stage	1	2	3	4
State	USED	USED	WORN	FAILED
Scope	7	67	75	42

It is observed from Figure 3 that the trend in process deterioration is visually similar in form to Taylor's Tool Life curves (Ahmed et al., 2016; Taylor, 1906), and can be approximated by a third order polynomial (not plotted). It is noted that although the initial period of rapid wear appears to occur in region A, this is not the case. The tool is pre-used, hence past the initial wear stage. The rapid wear visible in Region A is attributed to a delayed increase in cutting speed from 36m/min to the desired 52m/min, hence shifting the state of wear proportionally (Kundrák & Pálmai, 2014).

Also noted from Figure 3 is the recommended wear limit according to ISO 8688-2:1989. The standard recommends that HSS tools be replaced when their average flank wear reaches 0.3mm or when any local maximum is 0.5mm. The equivalent magnitude change in product CSA is 37.42mm^2 and was surpassed by the cutting tool after 142 parts. This indicates the cutting tool was utilised beyond the recommended limits and again highlights the problems with post-process investigations into tool condition. Little consolation lies behind the ability to point at a ruined part or tool and give a time of failure.

The results corroborate the earlier statement that the tool is pre-used and hence primarily in the latter stages of tool life. Stage 4 is identified as failed due to exceeding the ISO 8688-2:1989 recommended limit, and due to the tool breaking whilst machining of the last part.

5.2. Spindle Process Signal Output

Having identified the progressive process condition from the part geometry, it is possible to consider the in-process acquisition of SML signals. The output acquired is presented in Figure 4, illustrating the quantised nature of the data.

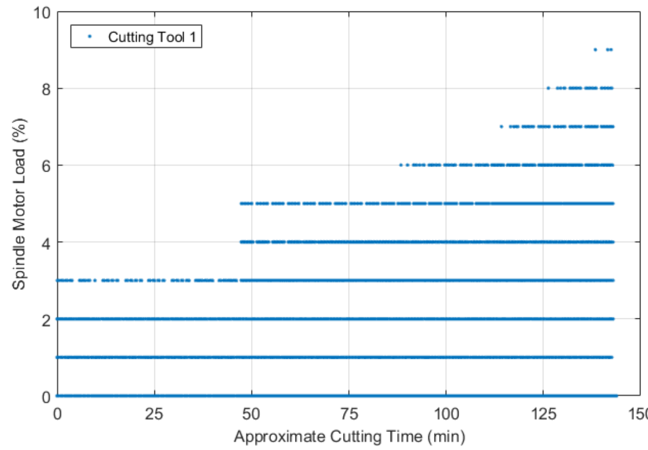

Figure 4. Scatter Plot of Original SML Output Data

The data was subsequently converted into energy consumption per part, presented in Figure 5.

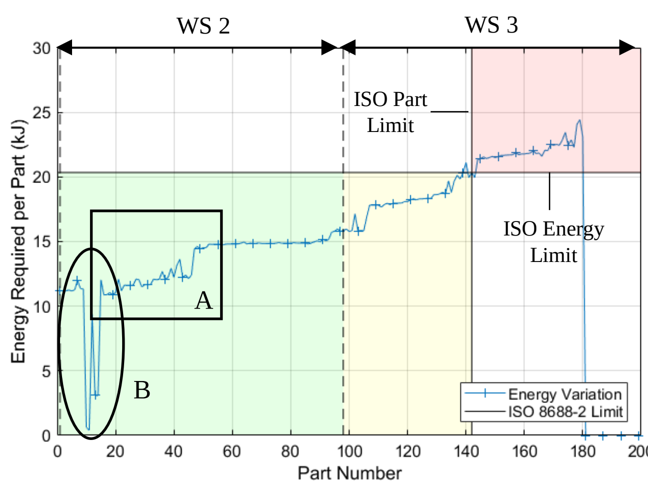

Figure 5. Estimated Stages of Tool Wear (SML)

Colour is again incorporated to emphasise the different stages of wear. Parts 0-98 indicate the first two wear stages (WS 2), whilst parts 99-200 indicate the final wear stage (WS 3). The ISO 8688-2:1989 limit is copied from the geometry data and is hence applied at the same part (Part 142). The equivalent energy threshold is assumed equivalent to the result for said part at 20.34kJ.

Table 5. Estimated Stages of Tool Wear (SML)

Stage	1	2	3	4
State	USED	USED	WORN	FAILED
Scope	1	97	45	42

It is observed that the gradual process change is similar to the variation in the part geometry and again marginally similar in form to Taylor's Tool Life curves. It is also noted that Region A, as observed from the geometry data, can also be identified from the SML data, further emphasised by an increase in process fluctuations. The quantised nature of the original data is still evident, with significant 'steps' in the data. This partially limits the effectiveness of the approach, as incremental changes will be lost.

Nevertheless, the approach also appears sensitive to process changes. Region B illustrates operator interference, where the process is stopped, adding unplanned machine downtime. The resulting process spike is significant, suggesting occurrences could be monitored. However as the information is derived from the spindle load, significant changes in spindle speed have the potential to produce similar results. Identifying the exact nature of the spikes in a practical application would hence require the consideration of additional information. If such information was available, this suggests the potential for improved estimations of machine availability.

5.3. Part-Process Correlation & Remaining Useful Life

As previously inferred, there is a degree of similarity between the changes in part geometry and the trend in SML output. Figure 6 illustrates directly the comparison between the geometry variation and the estimated energy range. The data has been standardized using Eq. (2).

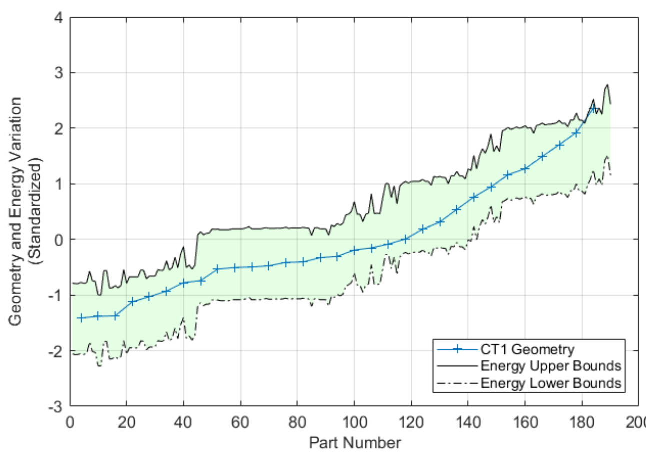

Figure 6. Change in Part CSA vs Estimated Energy Range

$$x_{std} = \frac{x - \bar{x}}{\sigma} \quad (2)$$

The SML output is presented as an area plot indicating the possible range, rather than an absolute value. This assumes that the quantised nature of the original output equates to the actual value being within the range of one equivalent unit (E.g. 4% has the value α, where $3.5\% \leq \alpha < 4.5\%$). This method hence considers the uncertainty in the given value.

It is observed that the progression in part CSA is within the estimated SML range for all parts. However, it is noted that for each part the range is relatively large (1.26 units compared with a maximum measurement range of 5.20 units). This indicates that the probability the CSA measurements will fall within the given energy region is high, irrespective of correlation. The uncertainty would be reduced with the acquisition of more precise data; however, in the absence of such data a more direct comparison is made (Table 6), assuming that the geometric approach is the gold standard.

Table 6. Classification of Geometric and Process Signal Results in terms of Wear Stages

	Geometry	SML Output	Difference
Stage 1	7	1	+6
MID Stage	40	43	-3
Stage 2	74	98	-24
Stage 3	158	164	-6

Where MID identifies the inflection point and hence the point at which a tool progresses from mostly new to mostly worn. Negative differences indicate the SML result is higher (In part numbers) than the geometry result.

It is considered that the SML output is more accurate than the geometry at identifying the pre-used nature of the tool, indicated by stage 1 ending on part one, however it is noted that this could occur due to the quantised nature of the data. It is also observed that the difference between the methods for three of the stages is equal to, or less than, one artifact (6 Parts). The acceptance of this error margin depends on the nature of the process and the actual difference in condition over as many parts. Stage 2 is identified 24 parts behind the equivalent in geometry variation. Further investigation is required to determine the significance of this gap.

The predominant limitation of this approach is that it utilises the variation in geometry as the most accurate measure of tool wear whereas research and industrial practice suggests otherwise. In industry tool offsets are applied to provide consistent component geometry. Such tool wear compensation will obscure the effect of wear from a geometry perspective. Hence, it is noted that the trends in geometric accuracy and process signal output are not anticipated to directly map one-another. In addition, the presented variations have been credited solely to a breakdown in tool condition, whereas in reality additional influences will come from the process, machine and operator.

The information presented serves as a preliminary investigation indicating the suitability for the process signals to be used as an alternative to geometry measurements.

6. CONCLUSIONS

This paper discussed the gap between academia and industry in terms of TCM and the possible causes for such. This identified some of the limitations in the current methods for TCM and the need for more robust solutions that not only allow for easy application within industry, but also progress away from the current craze for mass data. This is unless appropriate solutions are presented to manage and/or process said information.

A fresh look was taken into the acquisition and processing of signals existing within the machine tool architecture. The signals were adapted to consider the energy consumption over time and indicated that process variations are observable, despite the approach being limited by the acquisition of quantised data. It was also observed that the variation in process energy is comparable to measures of tool/process condition from post-process measurement of manufactured parts. This indicated a potential for the approach to offer an in-process (active) assessment of tool and process condition, enabling a basis for more accurate, reliable and repeatable machine operations. This would be in lieu of using geometry variation for the prediction of tool and process health.

It is acknowledged that further work is needed to support the analysis presented in this work, with consideration of additional process variables to further support the observations and assumptions made.

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