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ORIGINAL ARTICLE

Multi-sensor process analysis and performance characterisation in CNC turning—a cyber physical system approach

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Abstract High accuracy manufacturing requires the utilisation of advanced signal processing and analytics to monitor, manage, and control production processes. These systems vary in size, scope, and complexity and have traditionally required the skill of multi-disciplinary individuals, for end-to-end application. Current research trends in digital manufacturing aim to remove this complexity through interoperability solutions encapsulated in cyber physical systems. These systems provide a platform for real-time heterogeneous data acquisition, analysis, and distribution. The focus of this research is to demonstrate the application of a cyber physical process monitoring system within an industrial case study. Specifically, a multi-scalable signal processing and analytic system is developed, for both user-driven and semi-autonomous production decision support in CNC turning machining.

Keywords Process and condition monitoring · Cyber physical systems · Decision support · CNC turning

1 Introduction

To achieve high accuracy part dimensions, engineers have sought to control the factors influencing the machining process [1]. Influencing factors can be characterised by the cutting tool state and the material removal process conditions. The cutting tool state corresponds to the ability of the mechanism to maintain its operation effectively, i.e. cutting motions, and feeding motion [2]. The material removal process conditions corresponds to the fundamental cutting parameters of machining, i.e. cutting speed, feed-rate, depth of cut, tool geometry, work-piece material, etc. [2]. In order to meet the control criteria, engineers have utilised a variety of multi-sensory monitoring systems to identify optimal operating parameters [3], tool wear [4], tool breakage [5], machining chatter detection [6], and work-piece surface roughness [7]. However both influencing factors affect the same variables. Root cause analysis of the process can only be achieved through an understanding of the influences of both the cutting tool state and the material removal process conditions, in real-time, across the monitored variables in the system.

The complexity of achieving performance analysis of both cutting tool state, and/or the material removal process, is evident in the multi layered requirements of achieving process and condition-based monitoring [8] [9] [10]. However, currently, the digital age of manufacturing is aiming to remove this complexity through the development of reconfigurable cyber physical systems (CPS). This concept relies on the incorporation of decentralised interoperable cloud solutions in combination with advanced analytics and artificial intelligence, to create the innovative and intelligent machines of the future [1]. It has been theorised that this collaborative manufacturing technology trend will produce a fourth industrial revolution, noted as Industry 4.0 [11].

CPS provides a borderless computation and collaborative space for the creation and deployment of new interactive algorithms to assist in production control, quality, and management. Future research directions and challenges within cyber physical manufacturing have been identified as self-organisation, control aggregation of multi-dimensional data, symbiotic human-machine collaboration, and methodologies for supporting complex heterogeneous manufacturing [12].

Previous research undertaken by Morgan and O'Donnell [13] explored the integration of manufacturing process

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monitoring methodologies with a CPS. This research identified the migration of data acquisition, signal processing, and decision support tools and techniques within a decentralised cyber physical architecture. Central to this research was the design and validation of a semi-autonomous process performance characterisation system.

Continuing with this focus, this research identifies a means of achieving performance characterisation of both the cutting tool state, and the material removal process, in CNC turning. Continuous and discrete analysis modes are utilised, in combination with aggregated statistics. Furthermore, analytics will utilise multi-source real-time vibration data, which is intrinsic to a new and worn cutting tool. The resultant analytics provide contrasting process performance data for normal and abnormal machining operations.

The aim of this research is to further advance CPS development in relation to the migration of analytics and methodologies for supporting complex heterogeneous manufacturing, and human-machine collaboration. The resultant is a highly dynamic and scalable process analysis system for both online and offline performance characterisation of machine tools/manufacturing processes.

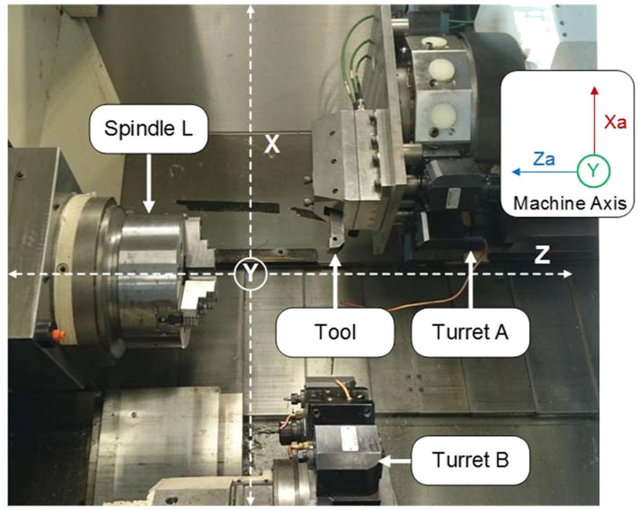


Fig. 1 OKUMA LT15-M CNC turning lathe

2 Cyber physical process monitoring system

The design and configuration of a cyber physical process monitoring system is detailed in [13]. Fundamentally, the system is co-ordinated through the setup of a decentralised signal processing chain which includes measurement, data acquisition, signal processing, and decision support/analysis. This setup requires the definition of (a) global goal of the processing chain, (b) localised goals of the chain components, and (c) interoperability architecture.

2.1 Global goal

In this work, the global or collaborative goal of the CPS is to characterise the performance of a monitored process. The process being monitored in this case is an OKUMA LT15-M CNC turning machine tool, see Fig. 1. Process performance is inferred from spindle and turret vibration, measured via triaxial accelerometers mounted on the left spindle, and A turret housings. Process states are inferred from electric motor currents measured via current transformers (CT), on the single phase spindle and axis motor windings. Performance characterisation will be achieved for both cutting tool state, and the material removal process.

2.2 Local goals

Local goals represent the systematic functional requirements of each component in the processing chain. The current functionality of the process chain includes data acquisition, data storage, signal processing, analogue-to-digital event conversion, event correlation, and performance characterisation. Multi-source data acquisition acquires: spindle vibration 12 Hz per axis, turret vibration 12 Hz per axis, and motor currents 3 Hz per channel. Data storage correlates the multi-source data streams and efficiently stores data for post process analysis. Parallel signal processing extracts features from process variables. Analogue digital conversion provides digital events from analogue signals via set limits. Event correlation identifies the machines operating sequence from multiple event inputs. The sequence iterations form windows of analysis for performance characterisation. Performance characterisation is achieved via time and frequency domain analytics that are correlated to the sequential machine operations, or user defined operating points.

2.3 Interoperability architecture

The cloud interoperability architecture defines the interactive capabilities between the process chain components. In this work, the Acquire Recognise Cluster (ARC) [14] architecture is utilised due to its high speed, high capacity, open data model, and local area network data interoperability. A detailed review of the ARC architecture is presented in [15].

The resultant decentralised signal processing chain/cyber physical process monitoring system is represented in Fig. 2. All software applications are executables (.exe) which operate independently. Motor current and spindle/turret vibration are measured and acquired via separate data acquisition devices. These devices communicate the data to data acquisition software adaptors. These signals are processed via ARC signal processing and fuzzy agents. Data is stored for post process analysis via the ARC database client. The machine tools operating sequence is identified via a central event processing

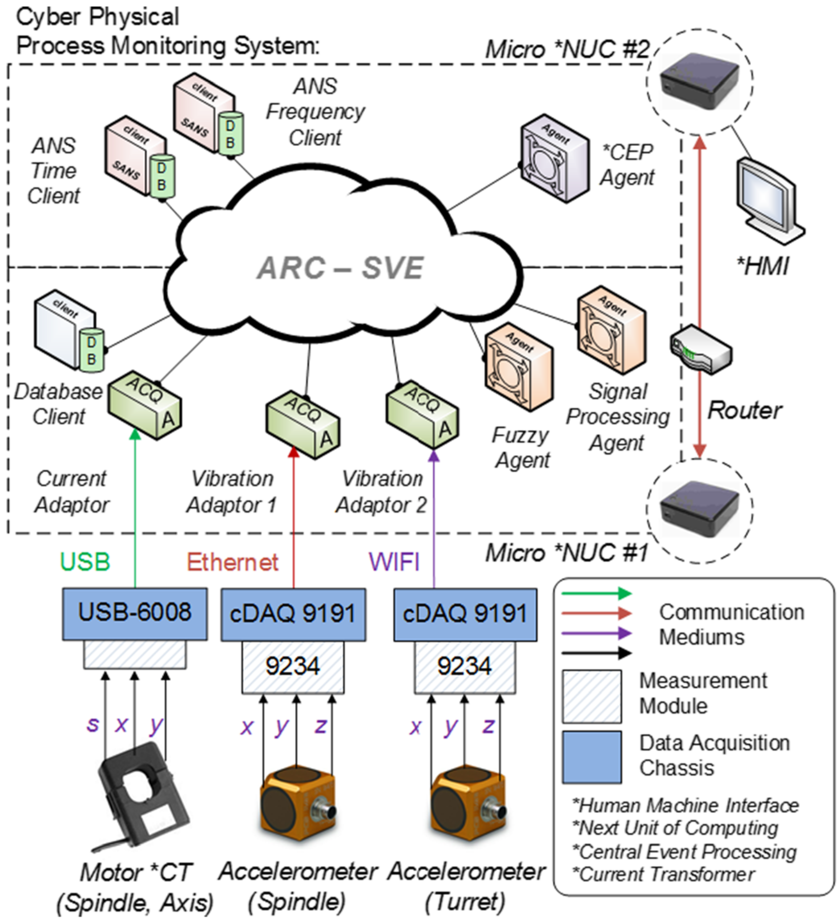


Fig. 2 Cyber physical process monitoring system

(CEP) agent. Process performance characterisation is achieved via ARC ANS time and frequency domain clients.

All cyber elements of the decentralised signal process chain are dispersed through two networked Next Unit of Computing (NUC) computers. The NUC's have a small form factor, 116.6 mm × 112.0 mm × 34.5 mm, providing a minimal impact to the industrial environment. Furthermore, the ARC-SVE enables data interoperability across a network. Multiple NUCs can be networked together to allow for high capacity decentralised computation.

3 Process analysis and performance characterisation

3.1 Prologue

CNC machine tools utilise a variety of direct and indirect measurements; power/current, vibration, acoustic emission, cutting force, etc., to identify a range of different production deviations; dimension accuracy, surface quality, cutting tool health, etc. [10]. The direct approach quantifies a variable, e.g. tool wear, from measurement [1]. The indirect approach quantifies a variable through deduction and correlation of auxiliary measurements. Direct approaches are highly accurate but limited in application due to access issues during machining. Indirect approaches are less accurate but are utilised more practically. However, new mediums are becoming available for direct measurement through smart tooling solutions [16].

In this work, the desired outputs of the system are non-invasive process performance characterisation of machine tool state and the material removal process, within industrial production conditions.

Vibration monitoring was selected, due to the fact that machines are not rigid bodies, but rather systems consisting of elastic components of relative motions from external and internal forces [17]. Meaning, a machines vibration are reactive to machine operations (independent) and material removal processes (dependant) [1]. Previous research has located accelerometers on the workpiece [10], on the spindle [18], and on the cutting tool [19]. By placing the sensors on the spindle and turret housing, the monitoring system becomes non-invasive [20]. The turret is free to rotate and utilise all the tools available. The workpiece can be freely replaced with modification to the measurement chain.

Vibration analysis involves the identification of deterministic and random vibrations, forced and free vibration, linear and non-linear vibration [21]. Detailed analysis can be made to determine the health of a machine and identify any faults that may be arising or that already exist [22]. Faults include unbalance, a bent shaft, eccentricity, misalignment, looseness, bent drive problems, gear defects, bearing defects, electric faults, oil whip/whirl, cavitation, shaft cracks, rotor rubs, resonance, hydraulic and aerodynamic forces, etc. The most fundamental analysis in vibration is the determination of amplitude characteristics in the time domain, and spectral distribution of the signal in the frequency domain [23].

3.2 Cutting tool state

The cutting tool state corresponds to the ability of the mechanism to maintain its operation effectively, i.e. cutting motions, and feeding motion [2]. The cutting tool state will be characterised independently, which is outside of machining operations via test programs. These programs will operate the machine under set parameters to establish normal operating responses.

This process is an example of preventative maintenance [24], where the condition of the machine tools state can be analysed for fault prognosis and diagnosis.

3.2.1 Setup

In this work, three independent CNC machine tool programs are utilised: (1) spindle speed, (2) z-axis feed, and (3) x-axis feed. Spindle rotation is set at 700 RPM, and at a Feed at 0.2 mm/rev. The process signals utilise a combination of both time and frequency domain analytics, with a continuous mode of analysis. Continuous analysis is user driven and requires human operation and interpretation. By defining start and stop points via a push button, a process signal can be recorded and analysed over a period of time.

3.2.2 Results

The spindle rotation is characterised in both time domain vibration and motor current Fig. 3. The x and z axis spindle vibration have similar responses: firstly a spike in vibration amplitude at the start of the operation, followed by a sloping decease, into a steady amplitude, and eventually a spike at the end of the operation. Diversely the spindle y-axis vibration maintains a set amplitude but also has a moderate spike at the end of the operation.

In order to identify the cause of the vibration responses, spindle motor current in connection with signal processing can be utilised to identify different operating states, as seen in Fig. 3(2). Firstly, a spike in inrush current [25] identifies the initial start of spindle. Next a high amplitude current is active during spindle acceleration. After which the current reduces as it approaches the desired speed and maintains this speed over the operation. The end of the process is characterised by a large spike in current which can be attributed to breaking

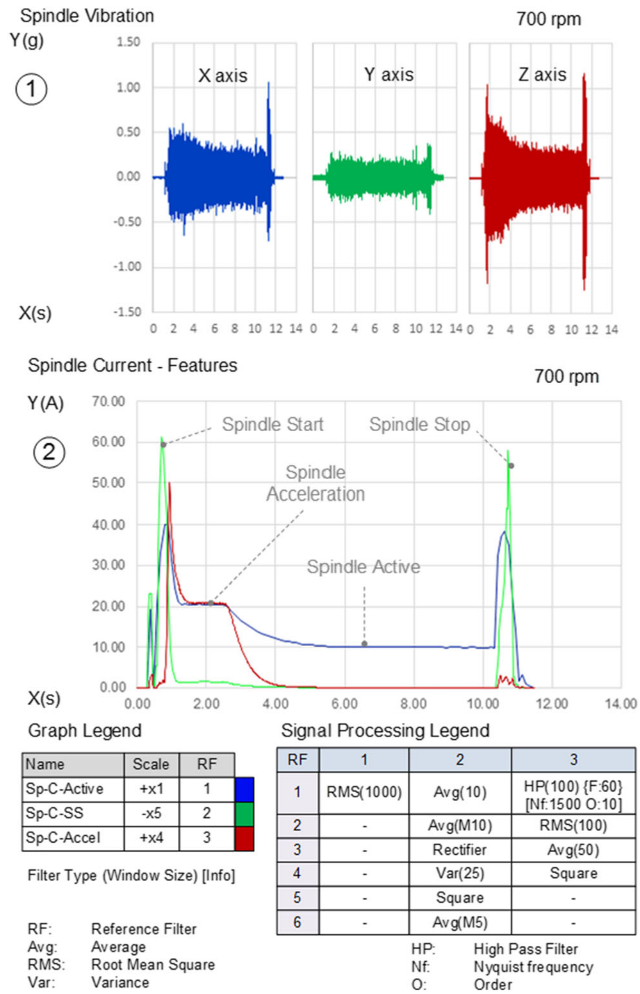


Fig. 3 Spindle rotation, time domain: vibration, motor current

and/or back EMF [26]. To further understand spindle vibration, the frequency response needs to be evaluated.

In this work, the OKUMA moves the spindle and not the turret for z-axis movement. Subsequently, the spindle frequency response will be reviewed during the z-axis set feed movement.

The z and x axis feed movements are characterised in the frequency domain, as seen in Figs. 4 and 5. A power spectra is utilised with a resolution bandwidth of 1 Hz across the full 6 kHz sensitivity range of the accelerometer. Continuous analysis identifies the power and frequency changes present across all axis during feed movements. The aggregate of the spectra identifies the average power across each frequency over the feed movement.

Both the spindle x and z axis vibration frequency responses identify a clear correlation to the varying speed of the spindle, with dominant high and low frequencies. Diversely, the spindle y-axis vibration response is constant on a single frequency. This dominant frequency area will be the focus of machining analysis, as it is the cutting axis of the machining operation. Movement in the z-axis is difficult to view due to the effects of

Fig. 4 Spindle vibration, frequency domain: z-axis feed

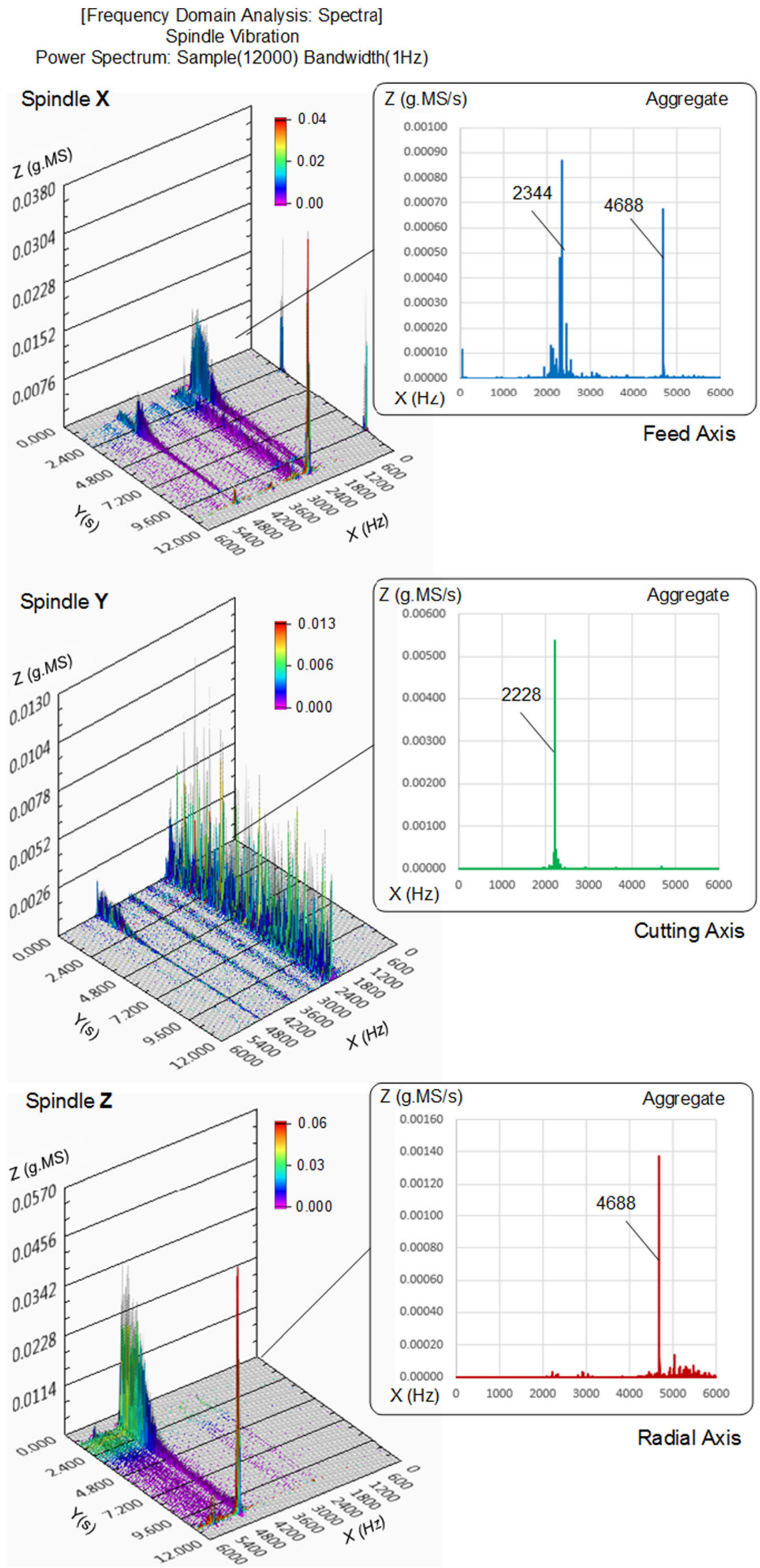
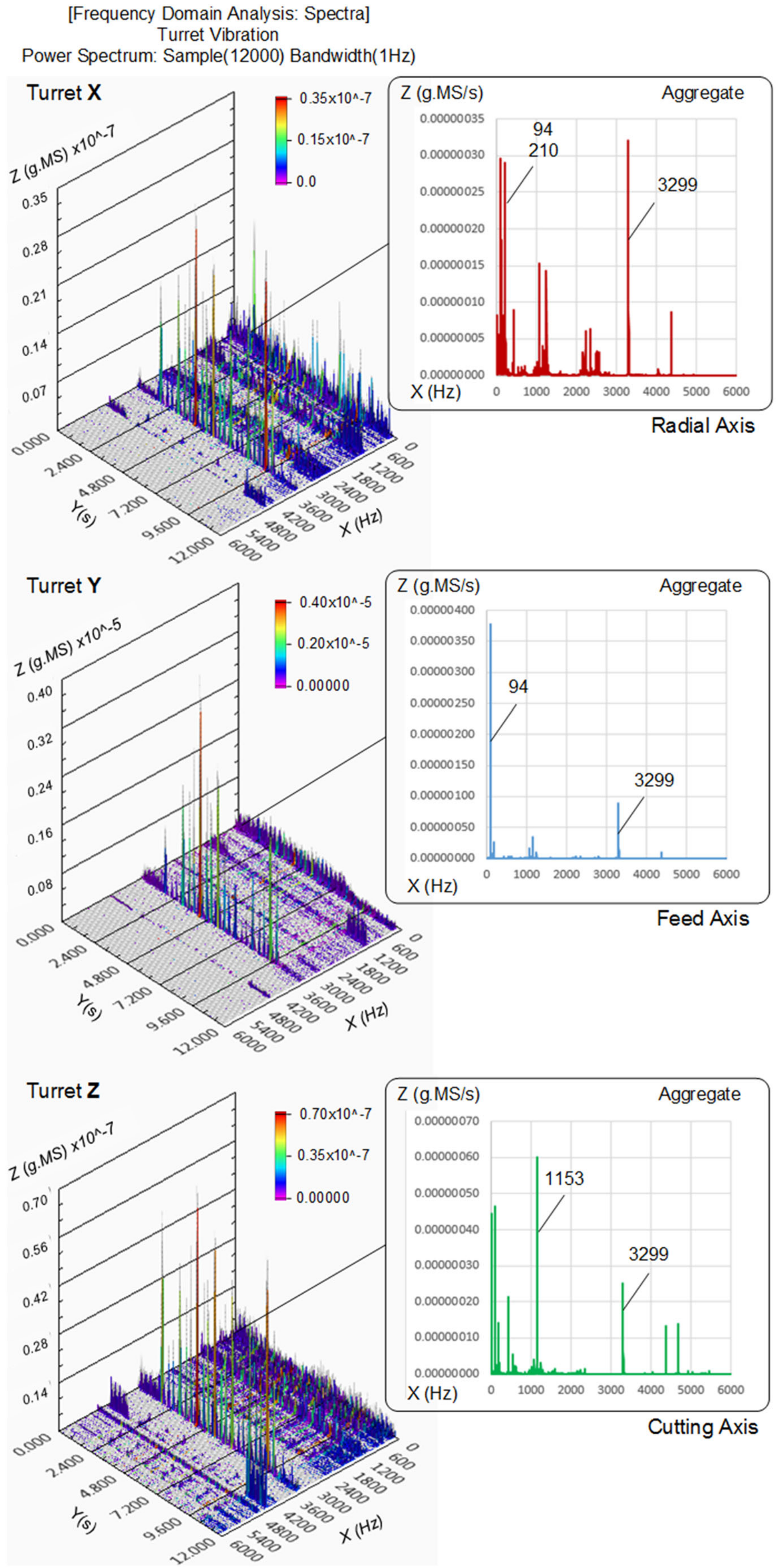


Fig. 5 Turret vibration, frequency domain: x-axis feed



spindle rotation. However, a clear low frequency power spike can be observed in the spindle x-axis, due to rapid movements to and from the home position.

Turret vibration consists of varying frequency and power responses to the x-axis feed movement across all measured axis. These frequencies represent the multiple resonant components on the turret, e.g. tools, turret housing, turret rotation motor, and feed motor/mechanical slide. The isolation of the turret from the spindle has resulted in minimal interference from spindle rotation, but low power due to the positioning of the accelerometer. However, low frequency x-axis movement is visible across multiple turret vibration axis.

3.2.3 Discussion

The metrics produced in this work have favoured continuous analysis for independent cutting tool state characterisation. The aggregate of this data produces a 2D metric for reference, which can be utilised for autonomous validation. However, vibration is highly sensitive and would require the review of a skilled engineer to diagnose the fault. Subsequently, the continuous measurement of vibration power spectra provides a 3D response of machining operations over time. This enables an engineer to observe the frequency and power responses and relationships to different operations.

Furthermore, the correlation of different data sources provides further advantageous perspectives on machine operations, for cause and effect understanding. Evidently, motor current measurement is a simplistic and non-invasive process mapping medium, which can assist in process and performance characterisation.

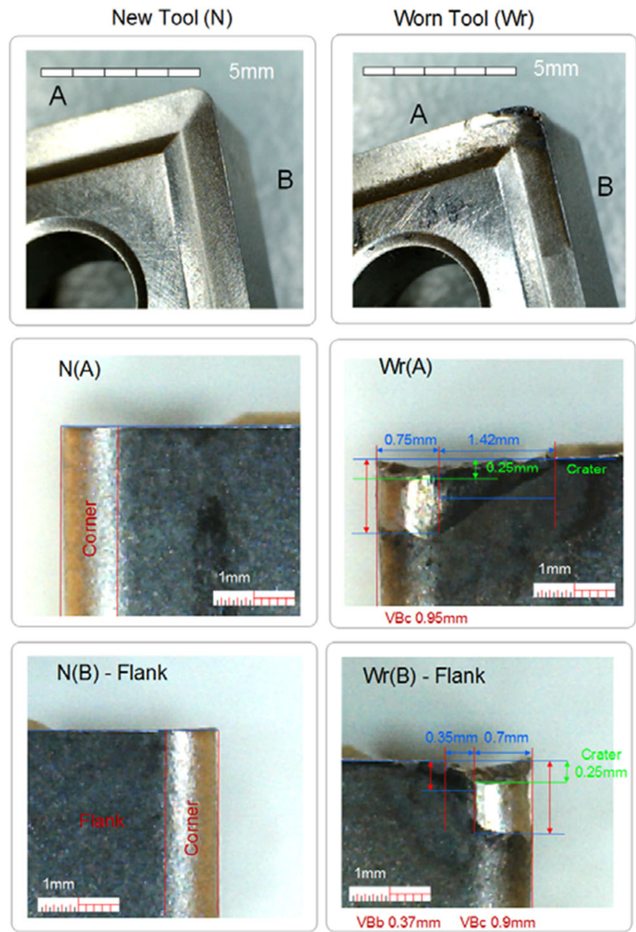


Fig. 7 Cutting tool tips [27]

The produced frequency and power metrics identified in this preventative maintenance process can now act as a datum point for normal operating criteria. Future measurements can

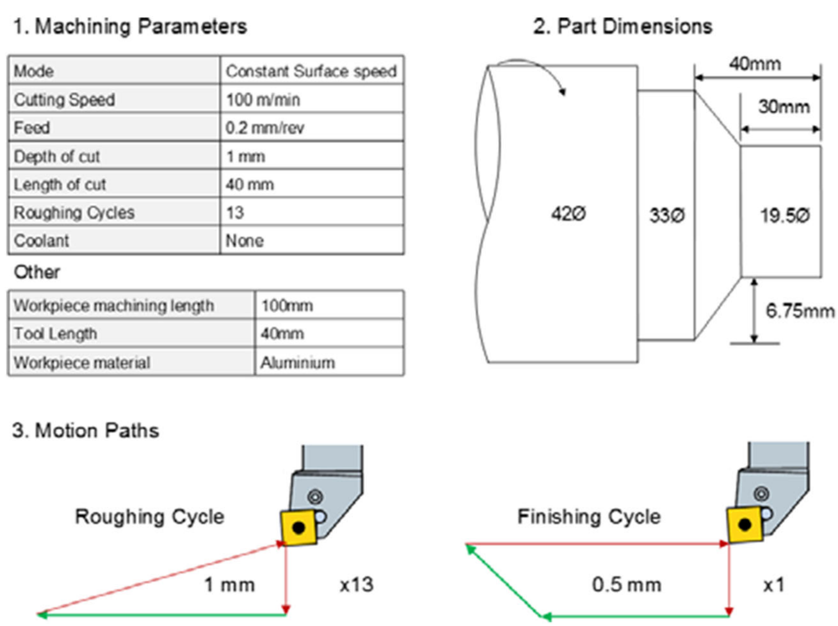


Fig. 6 Machining criteria

now be cross referenced for prognosis and diagnosis purposes.

3.3 Material removal process

The material removal process conditions corresponds to the fundamental cutting parameters of machining, i.e. cutting speed, feed-rate, depth of cut, tool geometry, work-piece material, etc. [2]. The material removal process will be characterised inside of machining operations, via production programs. These programs operate the machine under normal machining parameters for the cutting of a defined production part. Normal machining responses will be defined with the utilising a new tool tip, and abnormal machining responses will be defined with utilising a worn tool tip.

This process is an example of condition-based maintenance, where the condition of the machine tool state and material removal process can be analysed in-process and in real-time for fault prognosis [24].

3.3.1 Setup

The machining parameters are represented in Fig. 6(1). In this work, the machining operation is dry single point oblique cutting of an aluminium (6082-T6) workpiece, 42 mm in diameter and 200 mm in length. The workpiece is exposed a

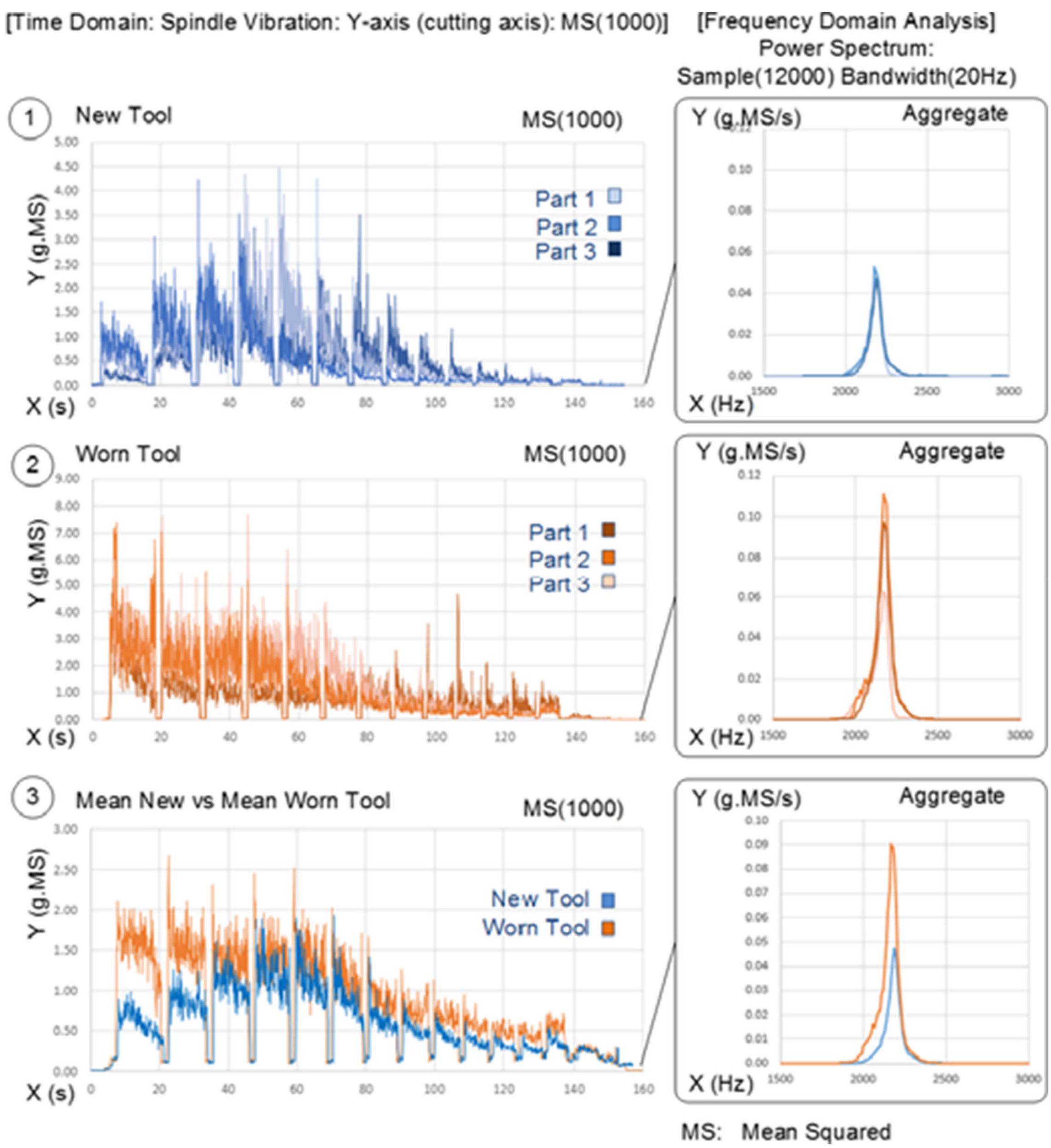


Fig. 8 Machining new vs worn tool, spindle vibration y-axis, time and aggregate frequency domain analysis

distance of 100 mm from the chuck and is pre-machined to a diameter of 33 mm over a length of 50 mm. Constant surface speed is utilised and set to 100 m/min. The production part dimensions are represented in Fig. 6(2). The machining motion paths undertaken in the process are represented in Fig. 6(3). A total of 13 roughing cycles are utilised, with a feed rate of 0.2 mm/rev and depth of cut of 1 mm. Finally, a finishing cycle will be utilised, with a feed rate of 0.2 mm/rev and depth of cut of 0.5 mm.

Two Sanvik SNMG 12 04 08-23 H13A tool tips are utilised during the machine of six parts. One of the tool tips is worn and contains both flank and crater wear [27], as seen in Fig. 7. Performance characterisation is achieved via a combination of both time and frequency domain analytics, with continuous, and discrete modes of analysis. Spindle y-axis vibration is analysed as it is the cutting axis of the machining operation.

3.3.2 Continuous analysis

Continuous analysis is user driven and requires human operation and interpretation. By defining start and stop points via a push button, a process signal can be recorded and analysed over a period of time. In this instance, the window of analysis spans the entire machining process of the part.

The time and aggregate frequency response of spindle cutting axis vibration is represented in Fig. 8. Both tools identify a pattern of increasing and decreasing vibration across rough cutting iterations. Furthermore, the aggregate frequency response in both cases identifies a consistent power area which is relative to the spindle vibration frequency. Comparing the average time domain response in both cases, as seen in Fig. 8(3), identifies a clear separation in performance. The worn tool has an initial increased power in the initial cuts, and a marginally increased power over the entire machining process. Furthermore, the aggregate frequency response of the worn tool identifies both a substantial increase in power, and widening of frequency excitation. This power and frequency response difference is also visible over time via the power spectra represented in Fig. 9. However, continuous spectra analysis is highly dense and difficult to interpret in the analysis windows time frame; 160 s = 3500 power spectrums × 300 spectral (20 Hz) = 1,050,000 data points.

The results identify a varying vibration response over time with both the new and worn cutting tools. This variation can be contributed to unmeasured phenomenon occurring in the machining process, which include temperature, spindle speed, and part dimensions. The friction caused in dry cutting continuously adds heat to workpiece. The spindle speed increases to maintain constant surface speed of the tool over the workpiece. The cutting cycles change the dimensions of the workpiece. Each of these variables is not fixed which results in a dynamic vibration response.

The effect of utilising a new and worn tool is visual in respect to the surface finish of the part, as seen in Fig. 10. The blunt worn tool has deformed the surface of the workpiece. The new tool has a clean surface finish and has received a thread in another machining operation.

3.3.3 Discrete analysis

Discrete analysis is process driven and requires human preconfiguration, but can achieve autonomous interpretation. By defining discrete points in the process with process driven events, a process signal can be recorded and analysed incrementally and repetitively.

To achieve discrete analysis of spindle vibration, a combination of spindle and axis operations are detected via motor current signal processing, as seen in Fig. 11(2). Primarily

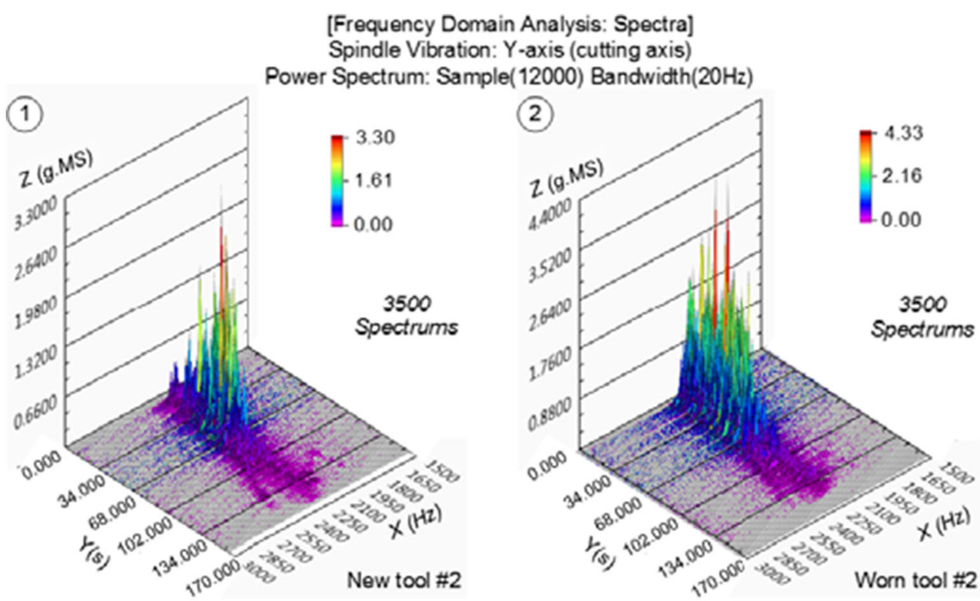
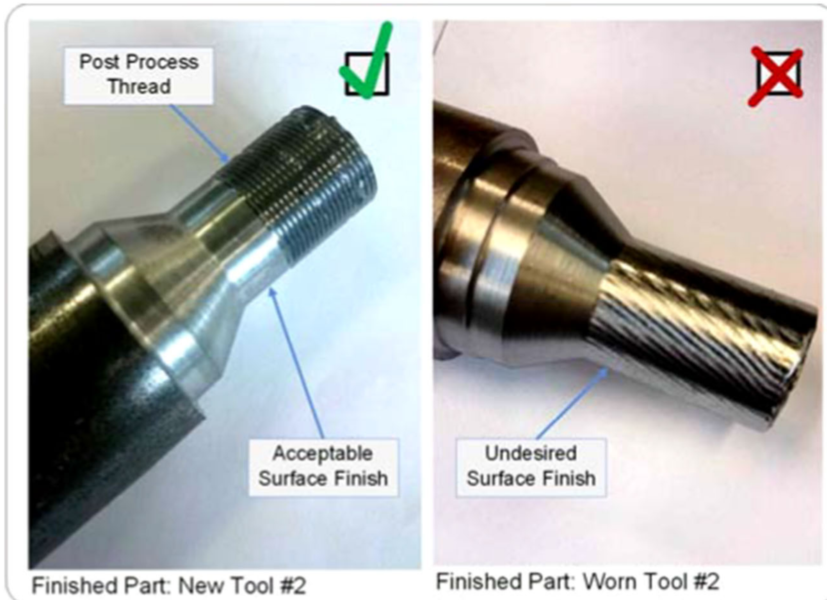


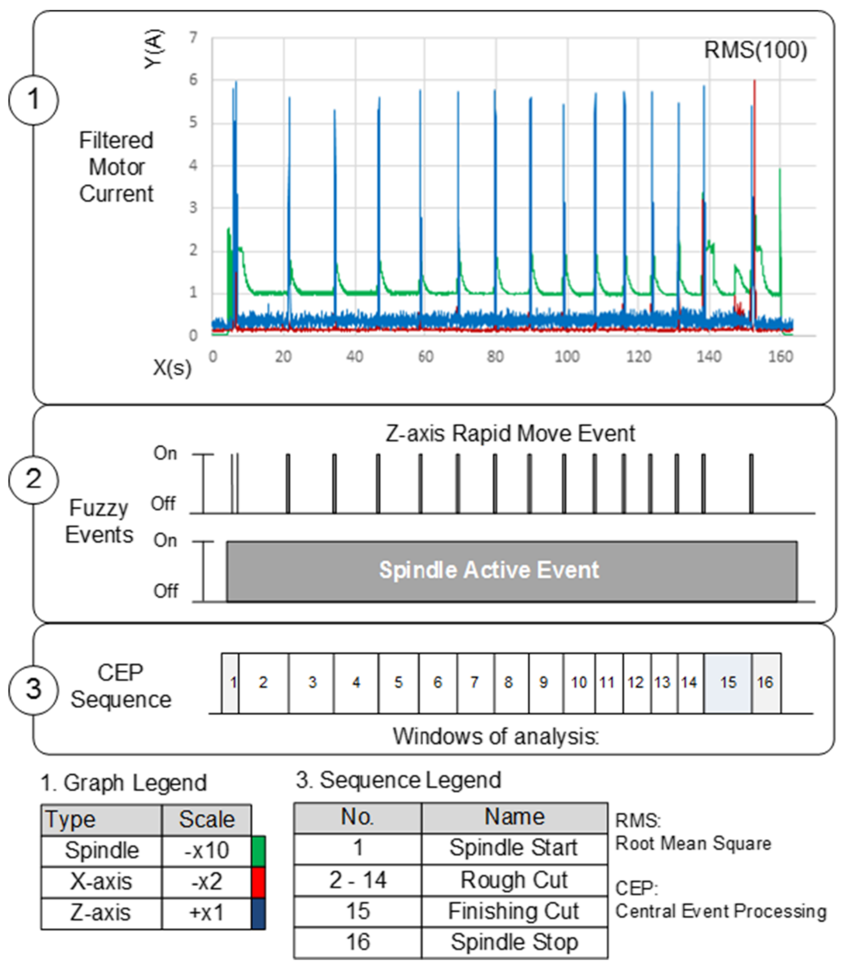
Fig. 9 Machining new vs worn tool, spindle vibration y-axis, time and aggregate frequency domain analysis

Fig. 10 Post machining surface finish



spindle rotation and z-axis rapid movements are utilised to define the start and end of sequential events. Motor current signals are processed via the signal processing agent, limits on the these signals indicate whether an event is active or inactive, which is processed by the fuzzy agent and outputted as Boolean events, as seen in Fig. 11(2). Event is acquired by the

Fig. 11 Discrete process sequencing



CEP-agent where the current sequential operating state of the machining process is identified, as seen in Fig. 11(3). The current sequential operation is available to any software application connected to the ARC data cloud, and enables reference points for discrete analysis. An in-depth review of this decentralised signal processing chain is represented in [13].

Frequency domain sequence analysis enables the generation of distinct power spectra that are correlated to machining operations, as seen in Fig. 12. The resultant spectra are less dense compared to continuous analysis, providing a clear visual representation of machining vibration. The results identify that all three parts machined with the new tool produce a similar frequency and power response over the sequence of machining operations. Furthermore, all three parts machined with the worn tool vary in frequency and power, but have noticeable similarities, such as the broad frequency excitation during the initial roughing cycles.

Previously, the comparison of continuous analysis signals required manual alignment for correlation due to the timing deviations in manual operation, i.e. push button start and stop

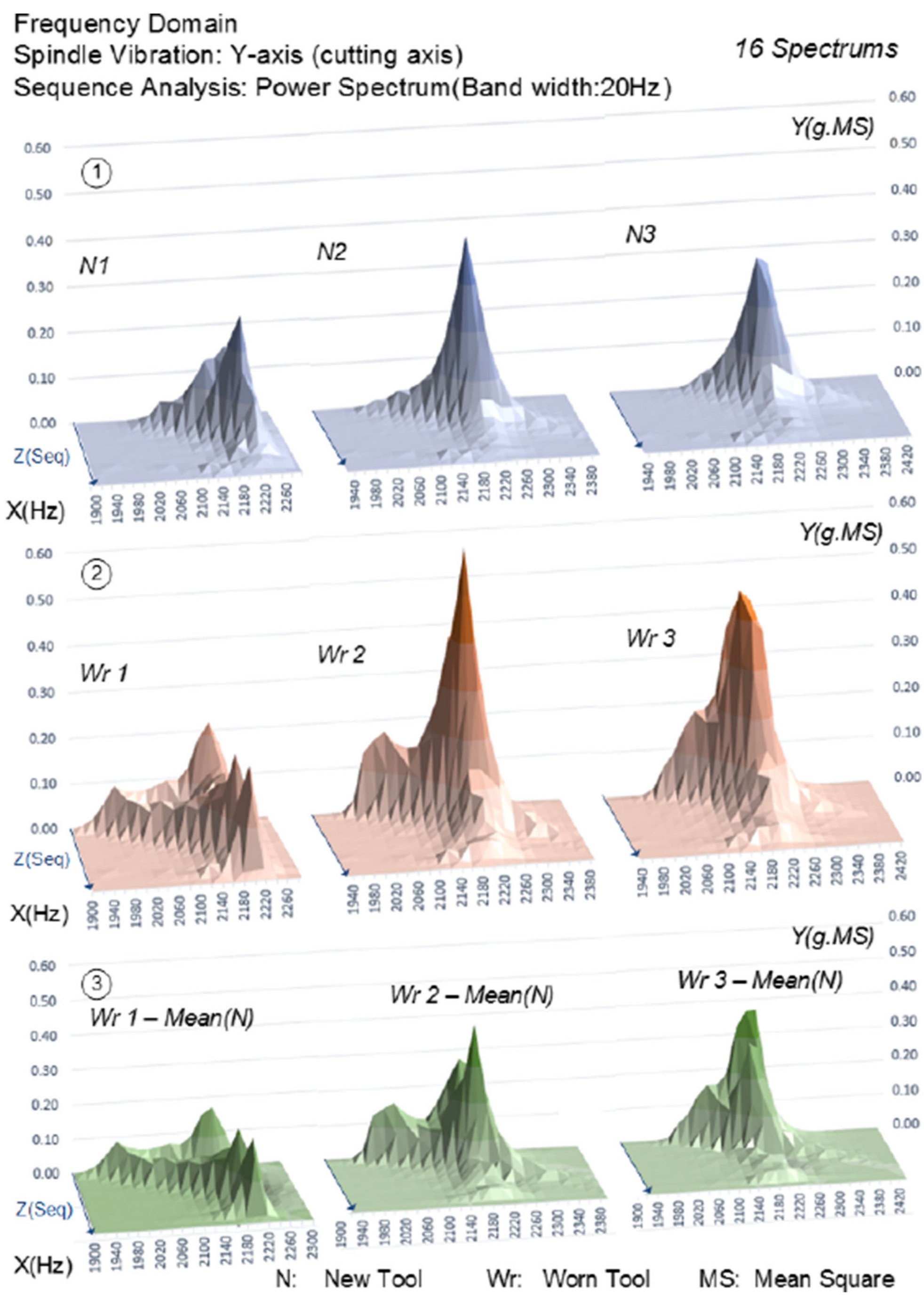


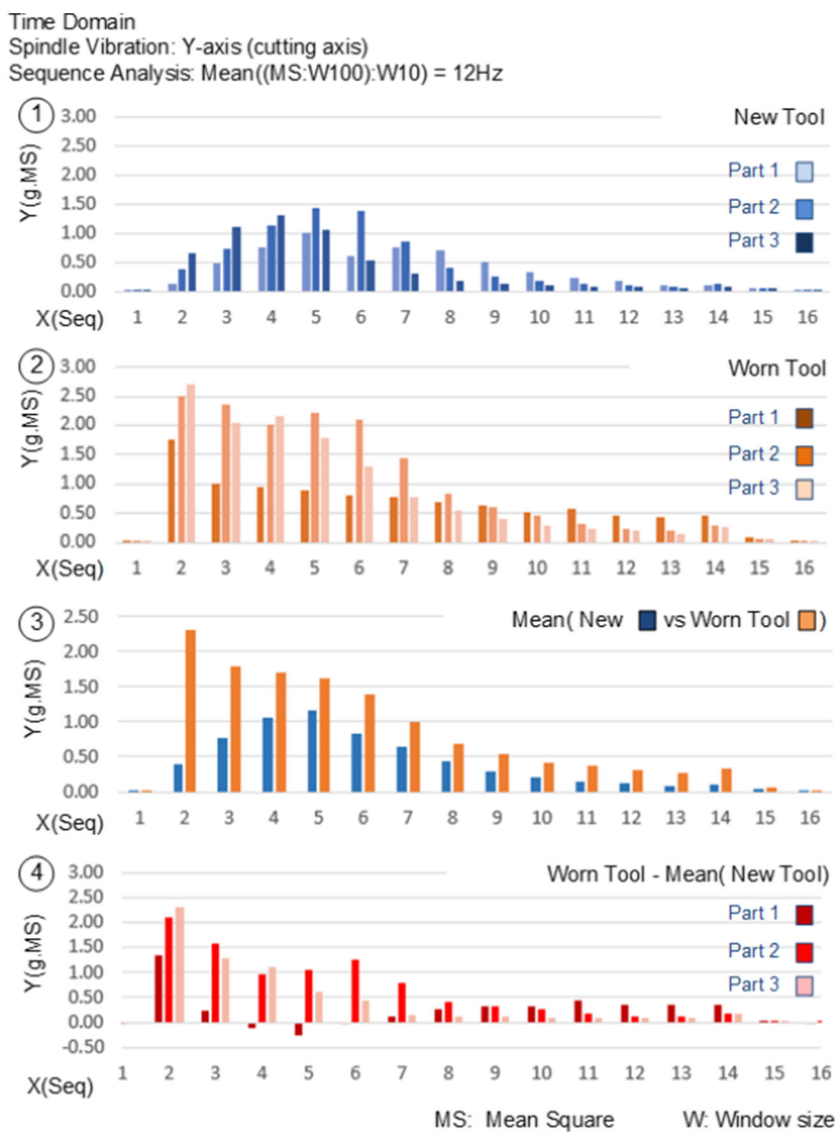
Fig. 12 Sequence analysis: frequency domain, spindle vibration y-axis

analysis. This problem is overcome in discrete analysis, as it is process driven enabling accurate and autonomous correlation. A benefit of this can be seen in the identification of deviation of current results compared to a specified reference value. This is achieved by setting a baseline reference and subtracting that value from new values obtained in-process and in real-time. An example of this can be seen in the setting of the baseline to the average frequency response obtained during new tool machining for each sequence. By subtracting the baseline during worn tool machining, a clear visual representation of vibration frequency and power deviation is presented in each sequence iteration, as seen in Fig. 12(3). The deviant power spectrums identify a clear abnormality in frequency and power response when machining with the worn tool.

Time domain sequence analysis enables the generation of discrete statistics, such as mean, maximum, minimum, stand deviation, which are correlated to machining operations. In this example, the mean spindle vibration MS value is obtained during machining, as seen in Fig. 13. In comparison to continuous analysis, discrete analysis has produced similar patterns of increasing and decreasing vibration across rough cutting iterations. However, uniquely the results are clear to interpret, and enable autonomous correlation for comparison. Once again, the time domain average new tool spindle vibration response can be set as a baseline reference, as seen in Fig. 13(3). By subtracting this baseline from current data in-process in-real-time, the deviation in spindle cutting axis vibration can be determined and visualised, as seen in Fig. 13(4). The results show a clear increase in time domain spindle cutting axis vibration for worn tool machining.

Furthermore, the time domain sequence analysis agent can process multiple signals in parallel. In previous work, vibration, tool force, and motor current was utilised for process characterisation [13]. But since all the signal processing chain is linked via the ARC data cloud, any process variable can be utilised.

Fig. 13 Sequence analysis: time domain, spindle vibration y-axis



3.3.4 Discussion

Both continuous and discrete modes of analyse provide profound process performance characterisation in similar and unique ways. Both methods provide an operator the means to identify machining performance, which in this instance is via spindle vibration. These metrics enable the operator to make an informed decision with the comparison of current data with normal operating data.

A visual validation of part surface finish is an indicator of a worn tool. However, the utilisation of performance metrics can identify the level of acceptance before the tool should be replaced, which reduces lost time in machining non-specification compliant parts, and reduces material waste. Furthermore, other failure modes can also be recognised such as improper tool or workpiece setup, or in more extreme cases motor faults and tool breakages.

The utilisation of continuous analysis in this work requires a human machine interface, push button, to specify the window of analysis. For future application, this operation could become more automatic through the integration of the spindle rotation event. This would identify the start and end of the machining operation, and initiate the analytics as required. However, continuous analysis would still require evaluation performed by an operator to identify the deviation in performance metrics. Potentially the aggregate of the data obtain within the window of analysis could be utilised for autonomous AI validation. However, aggregate analysis is a mean value, providing no insight into the cause of deviation within the process. Furthermore, depending on the process being monitored, aggregate analysis can be affected by interference from machine operations outside of machining actions, such as rapid axis movements and spindle activation and deactivation.

Discrete analysis provides multiples benefits to machine monitoring. It is process driven and once configured becomes autonomous in operation, with the option of AI validation. Process analytics are comparable as they are correlated to process operations. Furthermore, discrete analysis separates process operations, enabling the isolation of operations of interest. In machining, for example spindle activation/deactivation and rapid axis movements can be separated from cutting operations. Additionally, discrete analysis reduces the analytical data set enabling an effective means of process analysis and an efficient means for historic data archiving. The only disadvantage to discrete analysis is the increased complexity of process monitoring system operation. However, through utilisation of a cyber physical architecture, this complexity can be reduced as all tools required are open and reconfigurable.

4 Conclusion

In conclusion, cyber physical process monitoring systems reduce the complexity of manufacturing process analysis, through dynamic adaption, interoperability, and reconfiguration. Fundamentally, this was demonstrated by the application of a cyber physical process monitoring system, within CNC machining, to achieve continuous, and discrete process analysis through vibration, electrical motor current data, inside and outside machining operations. Elementally, the utilisation of a cloud architecture enabled the dynamic integration of multiple process variables, and higher-level analytical data streams. The open real-time environment has enabled the incubation of process specific analytics through configuration of dynamic signal processing modules. The outcome of this methodology and platform is the creation of a tiered process characterisation system, for manufacturing decision support, via traditional user interpretation and more advanced semi-autonomous AI.

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