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Multiple classification of the force and acceleration signals extracted during multiple machine processes: part 2 intelligent control simulation perspective

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Abstract Part 2 of this work looks at the simulation for the accurate control of multiple machine processes made on a machining centre. Specifically the models are based on controlling against two grinding anomalies; grinding burn and chatter, and for hole making; drilling tool wear and the onset of drill tool malfunction, which is also significant to severe scoring and material dragging. The work developed here takes the ideas of part 1 further where intelligent control based on the identification of force and accelerations in z axis time-frequency domain is applied. This work is significant to automated manufacturing, where observed anomalies significant to surfaces quality cannot be accepted and play an integral part to flexible automated manufacturing systems. The simulation models displayed in this part can easily be realised into prototype embedment promoting real-time control against unwanted surface anomalies for multiple machine processes.

Keywords Burn \cdot Chatter \cdot Force \cdot Accelerations \cdot Tool malfunction \cdot Feature extraction \cdot Wavelet transforms and simulations

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1 Introduction

There is plenty of literature looking at control for quality holes during hole making or, the control for achieving a superior ground surface. There is however very little literature looking at the control of two processes sequentially in the form of multiple processes. This part 2 concludes the work discussed in part 1 where the transfer of intelligent concepts into simulation models is carried out.

The following investigations give a background where traditional and intelligent control has have been applied to simulations and models alike. Such ideas are very central to the concepts reported here. For instance, a control regime for grinding is discussed by [1] where a dynamic model is used to provide varying horizontal feed rates based on cost functions correlated to weightings of process time and dimensional error. This dynamic model provided good results and materialised a 13% increase in surface parallelism. Some of the remaining error however can be attributed to thermal expansion of the workpiece, grinding wheel and machine; it should be noted grinding has an important thermal output component. Other works by [2] optimised the grinding DOC and table speed to ensure anomaly free surface as well as the best productivity was obtained. Such works are particularly similar to the work presented here.

Similar research to the dynamic feed rate control model is presented by [3] where the control of the spark-out grinding pass is maintained to ensure the surface roughness values are kept within acceptable limits. However, in controlling the surface roughness, there are additional factors that need to be controlled such as the machine stiffness, grinding deflection and wheel sharpness. Different grinding wheel topologies were investigated by [4] and the effects of various coolant applications. This is considered an important issue for both deflections and anomalies when considering the interactions

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between the grinding wheel and workpiece. Such profile deviations can be attributed to high burst temperatures during the abrasive process.

For control when fabricating holes, [5] investigates controlling the drill operation through the instantaneous monitoring of torque. A third-order linear model with time delay is identified and used in conjunction with an input/output poleplacement controller utilising gain scheduling. Such control authorities give a smooth operation for real-time environments [6] investigated two facets of monitoring where both the force and accelerations are extracted during drilling. Vibrations were considered critical for tool condition monitoring: identifying the onset of rapid malfunction. The work was based on the identification of frequency ranges significant to either bending or torsional effect where the spindle speed dictates if the lobe is either in or out of stability. Kim et al. [7] uses a dynamic real-time control for thrust force which ensures a better tool life and maintained hole quality. Such parameters are considered important for accuracy and tool condition monitoring.

The discussed research of grinding and hole making give ideas in terms of which extracted signals are more useful than others, the application of controlling the models are however distinctly different. Such considerations make way for a robust control system that requires the same extracted signals applied under different strategies when associated to the individual machining process. The next work looks at intelligent models and control where investigations presented by Haber et al. [8] looks at controlling the spindle feed rate which inherently controls the applied force during drilling. The control was provided by fuzzy rules to gain the correct level to maintain productivity and, at the same time ensure no breakages from incorrectly applied forces. Sheng and Tomizuka [9] investigated intelligent modelling of thrust force during the drilling process. It was discussed that 50% of all manufacturing is carried out in the form of drilling which suggests it is a significant process to control when considering multiple processes on a machine centre. Through intelligent modelling, the overall objectives were to achieve the best removal rates and, at the same time, obtain hole quality with maintained precision/accuracy. Other works looked at wavelet transforms with fuzzy-NNs used to determine the wear states from correlated AE during drilling 40Cr steel [10]. These last two works are interesting where requirements to control against unwanted surface anomalies are becoming more common.

Currently there is very little or no work looking at multiple anomalies for multiple machine processes which is why it is reported in part 1 of this work and further developed here in part 2. Very similar to grinding, the force, accelerations, temperatures, power and AE can all be used to monitor the onset of drilling tool failure (scoring, dragging and tool malfunction); however, the work presented here focuses only on force and accelerations. The main investigation objectives of this paper are as follows:

- Produce an intelligent simulation model for monitoring grinding signals detecting multiple anomalies.
- Process control for spindle feed and table speed based on force and acceleration signals as used in grinding.
- Produce an intelligent simulation model for monitoring drilling signals detecting increased tool wear and the onset of drilling tool malfunction.
- Process control for spindle feed and table speed based on force and acceleration signals as used in hole making.
- Display effective flexible multiple machine process control based on typical surface anomaly scenarios.

The investigations of multiple control for multiple machining processes look at different conditions namely burn, chatter and tool malfunctions through force and acceleration signals which is both novel and provides a different focus in obtaining intelligent automated control of future flexible manufacturing systems. This part of the work specifically concentrates on the simulation model which could easily be realised into a prototype embedded system. The rest of the paper is organised into the following sections: (2) Motivations for such technology, (3) Multiple process control simulation, (4) Results: model signal outputs, and (5) Conclusions.

2 Motivations for such technology

2.1 Limitations to automation

It is easy to figure out that current technology is unable to automate all the desired tasks. What is the reason however for this problem? Which are the current limitations? Many operations using automation have large amounts of invested capital and produce high volumes of product, making malfunctions extremely costly and potentially hazardous. Therefore, some personnel are needed to ensure that the entire system functions properly and that safety and product quality are maintained.

2.2 Current limitations

Many roles for humans in industrial processes presently lie beyond the scope of automation. Human-level pattern recognition, language comprehension and language production ability are well beyond the capabilities of modern mechanical and computer systems. Tasks requiring subjective assessment or synthesis of complex sensory data, such as scents and sounds, as well as high-level tasks such as strategic planning, currently require human expertise. In many cases, the use of humans is more cost-effective than mechanical approaches even where automation of industrial tasks is possible. Overcoming these obstacles will ensure adaptable automation of complex scenarios will become more common place.

"The question for is no longer, 'Can I run this job unattended?" "The question now is, 'How long can this job run unattended?" [11]. This demonstrates human supervision is still required even after a long time of automated work, and also what interconnection of all machines are a step to overcome such problems. Tools also may be added to perform light cuts, finish passes, deburring, or chamfering to eliminate secondary operations during the day shift. Some systems incorporate tool breakage detectors as a next line of defence, forcing the system to shut down in the event of a tooling mishap.

2.3 Work focus

This investigation addresses the problem of automated manufacturing processes using customisable machine centres with intelligent control. Currently, the state of the art has dedicated process control for spindle and table speeds. Such systems, however are not fully automated and customisable. Therefore, machine operation during the "lights-out" phase does not exist and will not exist with the current thinking. The problems associated to achieving this status is down to the necessary setup conditions and, can the machine centre carry out all the required machine processes for part completion? Can intelligent control systems cope with all the presented uncertainty to ensure safe and accurate use? Are the sensor systems affordable and promote easy integration for end use? Moreover, specialised controllable machines are taking to the market which specifically look at controlling one aspect such as follows: feedback of vibration or force, resulting in a change of machine parameters; if sensor goes beyond limits, the machine will stop due to potential tool failure; if the part persists on going out of geometrical tolerances, interaction with machining parameters can adapt to ensure the geometrical tolerances are still met. To "bridge the gap", there needs to be more generalised solutions adapted to control many different processes and, at the same time, control against unwanted anomalies.

Wojciechowski et al. [12] investigated the machining of titanium alloy where low heat conductivity at high spindle speed is often associated with this difficult to cut alloy. Process damping was exploited to improve the limited productivity at low cutting speed. The investigation evaluated wavelength performance of process-damped milling under irregular tool geometries. In summary, controlling the parameters spindle speed and feed rate for irregular milling tool geometries can be used to suppress the chatter by exploiting the process damping behaviour, ultimately improving machining productivity. In other work, [13] looked at a mass spring damper model developed from the processed frequency domain acceleration signals of ball end milling. Similar to the other work, such models were compared against empirical results; the models would then be used to predict tool deflections and counteract through corrective dimensional measures (changing cutting depth of cut and feed rates).

Specifically applied to grinding when under certain conditions with high feed velocities or the use of very dull grinding wheels, the workpiece's rotational movement becomes unstable, resulting in irregular velocity accelerations that can eject the part very suddenly and compromise machine safety. The risk of rotational instability can be reduced by using a regulating wheel with a higher coefficient of friction, using a work blade with a steeper angle and minimising the workpiece centre height as was investigated by Hashimoto et al. [14-15]. Such ideas will be exploited here; however for automation, the change of feed, wheel speeds and DOC to maintain stability until essential dressing has to be carried out via sufficient dressing ratios. Work-regenerative chatter vibration phenomena has been studied by many researchers [16-20] to identify the excitation frequencies that should be avoided to minimise system deflections and how the setup parameters should be selected to suppress the effect of resonant and forced machine vibrations around the wave frequencies where lobing instability may occur (50-100 Hz).

The investigated work here focuses on key anomalies to identify and control against. A measure to provide the first parts of intelligence in integrating with other complex systems to ultimately realise; fully automated flexible manufacturing systems, thus ensuring industries have more available flexible options to become more competitive. Using a sensor fusion approach, the accelerations and force are correlated to empirical results which verify chatter and burn based on physical measurements. For commercial systems, certain parameters have to be maintained; however, it is possible to change some parameters to gain completion before dimensional inaccuracies and material integrity are compromised.

3 Multiple process control simulation

This section looks at multiple control through segmented intelligent systems that utilise the same input signals, namely force and accelerations. The first model looks at indentifying drilling anomalies: tool wear (significant of scoring and burrs) and onset of drill tool bit malfunction. The second model looks at identifying grinding anomalies: chatter and burn.

3.1 Drilling anomalies model

The subsystems Fz (Fx) and Az (Ax) are displayed in Fig. 1 where both processing subsystems are essentially the same with different generic gains when compared with the control system of grinding. Therefore the flow chart of Fig. 4 is



Fig. 1 Signal selection for different drilling tool phenomena

essentially the same however applied to drilling as opposed to grinding.

Figure 1 displays the signal selection system based on the different types of phenomena needing to replicate; for example, tool 2 is a set of holes cut optimally and with no real onset of malfunction, tools 1 and 3 were different drilling tools that endured different types of malfunction: overloading and increased wear due to poor coolant delivery (no through coolant), respectively (in the case of drilling coolant either through coolant or none through coolant is selected: for such difficult to cut alloys without using through coolant is significant to promoting failure).

Wavelet processing of the drilling model is the same as that applied to grinding (Fig. 2). The same input signals are also used as in grinding: force and accelerations in the z direction (*thrust* and *DOC* direction). Figure 2 only displays the module for force processing which is different to the grinding model, where less processing steps are necessary. This is due to the clean nature of signals, where the straight forward identification of force trajectory mapping is necessary for the accurate determination of a malfunctioning drilling tool. The two drilling malfunction phenomena show drilling malfunctions where a quick, steep trajectory is observed for a tool with excessive loading from the onset, and secondly, a gradual trajectory with a sharp rise at the onset of failure based on a tool with poor coolant delivery. This force-processing element was considered more significant for accurate distinction of the drilling tool malfunction. Also significant for correct verification were the accelerations processing part where increases in accelerations were significant to a malfunctioning drilling tool. This allows for a more robust control scheme, allowing for a safer approach, where sporadic condition is duly recognised by cross referencing data sets. Only when both force and acceleration levels increase beyond maximum levels is when the machine is stopped to prevent tool failure.

3.2 Grinding anomalies model

This top layer of the grinding model (Fig. 3) has several secondary level processing elements such as the selection of signals (similar to Fig. 1) representing signal data of replicating phenomena: chatter or burn, both the force



Fig. 2 Wavelet filtration and signal conditioning followed by force level control



Fig. 3 Top level model for grinding anomalies control: chatter and burn

and acceleration processing modules are described in Fig. 4. The *DOC* (in SI units) is used to select the corresponding signal data which when coupled with no/ coolant signifies whether the signal phenomena is that of normal grinding, chatter or burn.



Fig. 4 Flow chart of sub systems FXDSPnCont and Subsystem_Az listing the simulink model functionality for grinding process control

Looking at Fig. 4 in greater detail, the DOC is selected calculating the associated MRR with other parameters taken into consideration. The MRR then links to a specific set of signals based on total job required (number of holes or machine grinding passes). These signals then pass through the wavelet signal processing [21] block (wavelet function Db 4 and 4 levels) providing filtration enabling stable salient properties for both the force and acceleration signals. First of all, the force on the left passes through certain conditions when greater than the set threshold (F_{I}) will mean the changing of *feed rate* and DOC. If however the trajectory rate of the force signal increases above a certain threshold (F_T) then further feed rate and DOC changes are executed. Further checks are made through the use of a hybrid classifier system (A*) of combined CART and NN [22] providing whether the levels are over an acceleration threshold for burn or chatter. In addition, further chatter processing (A*) detects a chatter pattern of inherent increase followed by a decrease of force signifying a decoupling effect due to the chatter phenomenon (for this condition, coolant is activated along with dressing ratio suppression), see previous work for more in-depth analysis of the phenomena [23]. For further verification, it would be possible to use $F_{\rm Y}$ and power as dimensions as they too are sensitive to chatter and burn phenomena.

For decisions within the control block, the input signals and machine constants provide values for standard grinding equations where outputs: specific energy, spindle energy, torque, and force give indication to the current conditions: normal or abusive. Output control variables such as *DOC*, *feed force* and ultimately, whether the machine should be stopped are sent for execution. Taking into consideration the functionality of Fig. 4 provides the control throughput for allowing machining to continue, continue with *feed speed* or *DOC* intervention, or stop if chatter or heavy burn (acceleration high levels) is detected.

4 Results: model signal outputs

This section looks at the model outputs starting with the drilling model followed by the grinding model. Such outputs are based on high-fidelity input signals which signify the phenomena of interest.

4.1 Drilling control simulation output

This section displays the input and output signals for the drilling conditions of excessive loading (drill tool 1) and increased wear due to poor coolant delivery (drill tool 3). Drill tool 2 was used for normal hole making (Notice tool 2 was executed first before the anomaly scenario).

The same approach was applied as in the grinding model where the input signals were filtered to ensure trend type pattern entered the processing systems to detect which phenomena was taking place. Figure 5 displays the tool condition 1 and 2 where tool 2 was the good tool operating normally and could have gone on to produce more holes, tool 1 however, was a tool with excessive loading over the limits for the designed tool and material. The sequence started with signals

Fig. 5 Drilling simulation significant signal inputs both unfiltered and filtered, respectively: force and accelerations for drill failure (drill 2 then drill 1 configuration) replicating tool 2 then tool 1, and very early into tool 1's cutting sequence, the detected force and accelerations were deemed at, and increasing above the limits for drill malfunction. Figure 6 displays the control sequence with and without control (closed and open loop, respectively). The closed loop control can be seen by the dotted lines where the combined decision processing (F_Z and A_Z) is when the machine is stopped for tool swap out (if no control is present (open loop) then the machine continues to process the presented signals: solid line significant of tool malfunction). Figure 7 displays the input signals of force and accelerations for the second drilling condition: malfunction from poor coolant delivery. Such phenomenon is detected when looking at Fig. 8 output signals where the dotted lines are representative of tool stop condition (both force and accelerations have to be over and above a set condition). The sequence for Fig. 7 input signals is based on the good tool, tool 2 followed by tool 3 (a drilling tool with inadequate coolant delivery).

4.2 Grinding control simulation output

Figure 9 displays the input data for both the force and accelerations before and after filtration. Such signals have been setup to mimic normal grinding then the onset of chatter followed by the chattering condition. Figure 9 is a grinding run through of typical grinding passes that turns into chatter



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through lack of applied dressing ratios and therefore simulates a real grinding case. This approach of feeding real scenario data allows control prototypes to be produced based around scenario-driven conditions. For the force signals (Fig. 9) with greater levels of filtration, the unwanted harmonics were removed.

Figure 10 displays the output control signals where the combination of signal control data from input force and acceleration signals are significant of the chatter condition (the individual control signals are apparent for force

(Fig. 10 top) and accelerations (Fig. 10 middle)). At this point, the combined control (Fig. 10 bottom) would stop the grinding process and force intervention to carry out essential maintenance dressing. Force and accelerations chatter ID signals are significant to output control signals initiated after surpassing measured force and acceleration levels. At the onset of the chatter condition, the system will reduce the feed rate to suppress vibrations however the inevitable stop condition will occur if no dressing is carried out (different signals are selected for respective parameter

Fig. 7 Drilling simulation significant signal inputs both unfiltered and filtered respectively: force and accelerations for drill failure (test 2 and 3 configuration)



Fig. 8 Drilling simulation combined output control for force and acceleration: open and closed loop (tool 2 and 3 configuration)



changes). Such chatter occurs due to the fact the wheel loads more and more, becoming less sharp, and thus promoting inefficient grinding phenomena: namely rubbing and ploughing.

Figure 11 displays similar input signals to Fig. 9; however, these signals are simulating the grinding burn condition. Again the unfiltered and filtered signals are displayed as showing the types of input scenarios for normal grinding, the onset of burn and, the burn condition. At the onset of the burn condition, the

system will slow down the feed rate and decrease the DOC to try and suppress the phenomenon. The unwanted phenomenon is also promoted further from reduced dressing ratios. Such burn occur due to the fact the increased wheel loading causes it to become less sharp, promoting inefficient grinding (rubbing and ploughing), which is a by-product of temperature at the cutting/workpiece interface. The filtration signals of accelerations display salient properties of the burn condition which can be more easily identified by classifier technologies.

Fig. 9 Grinding simulation signal inputs both unfiltered and filtered, respectively: Force and accelerations for chatter condition



Fig. 10 Grinding control output force and accelerations detections are both high for confirmed chatter (see *bottom*)



Figure 12 displays the control output for DOC and feedrate intervention where the dotted line displays closed loop control and where the detection of the acceleration levels surpasses limits between normal grinding and the onset of grinding burn. At this point, the machine will modify its parameters, and if conditions continue, the machine will stop for essential dressing/maintenance to be carried out. The levels of low, medium and high (low and medium are considered to be normal grinding conditions) are in respect to experienced voltage amplitudes and energy densities of the presented signals. The tracking control signal passes the threshold from medium to high and after satisfying the trajectory slope and level over a

Fig. 11 Grinding simulation signal inputs both unfiltered and filtered, respectively: force and accelerations for burn condition



Fig. 12 Control outputs for suppression of grinding anomalies: changing in DOC coordinated with change in feed rate



set duration; the control reacts to enforce the stop condition. Thus, the control reacts a little after passing the high threshold to ensure the correct action is carried out based on the onset phenomena instead of a false positive condition (incorrect).

5 Conclusions

The work carried out in this paper was focused on multiple process control. For example, when aerospace power plant companies are manufacturing turbine discs, there is need for multiple processes, such as drilling and grinding. These companies have very tight schedules based on the demand outweighing the supply capabilities. They have introduced night shifts and weekend working, however, such strategies eat more into indirect labour costs. To get around these difficulties, there is a requirement for less staff, albeit staff that is highly skilled to oversee automated process. To ensure such automation or "lights out" manufacturing, significant breakthroughs in robust control are necessary. The discussions in this part of the work address this short fall is the form of developing intelligent models and simulations. Once a phenomenon has been detected through sensing capabilities, the system provides a control output of what options should be carried out next: from speed or parameter intervention, to ultimately stopping the machine requiring essential maintenance, such as dressing or tool swap out.

The results given in Section 4 display that the models of Section 3 can react to different conditions and can react in a robust manner. The models in Section 3 also display how the complexity of multiple process control can be established from using focused specific models (drilling and grinding) that run independently from standard CNC machine calls. Such models can increase in number based on more machining processes or necessary control parameters. Both the investigated multiple control models in this work use force and acceleration sensing technologies, which ports across to each simulation system seamlessly where such sensing signals (accelerometer and force in z axis) are considered to be the most sensitive to machine signal variations. That said, the models could easily be adapted for increased sensing dimensionality. The findings of the paper were based on previous work albeit integrated through simulation models based on the extracted signals. For hole making, the importance of mapping complex force levels as well as the increased trajectories is captured through intelligent algorithms namely CART and NNs that when combined deliver an ability to permit further machining or intervene with mandatory action. The burn condition of grinding increases in both force and accelerations which again is captured by both CART and NN algorithms. The burn condition control following for accelerations was particularly difficult to implement as the onset condition of burn occurred further into the machine pass hence why the control action occurred well after the medium to high acceleration threshold. The use of extra dimensionality in the form of acoustic emission or power could provide more confidence with more sensitive reactive components.

Future work will look at controlling more unknowns during the multiple machine processes. The focus of preventative and predictive control will also be investigated through more advanced simulations where curve type responses (more overlapping conditions) will be followed instead of on/off sharp control directives.

References

- Hekman KA, Liang SY (1998) Feedrate optimization and DOC control for productivity and parallelism in grinding. Mechatronics 9:447–462
- 2. Hekman KA, Liang SY (1998b) Flatness control in grinding by depth of cut manipulation. Mechatronics 8(4):323–335
- Chen X, Rowe WB (1999) Modelling surface roughness improvement in grinding. Proceedings of the Institution of Mechanical Engineers Part B-Journal of Engineering Manufacture 213(1):93–96
- Razavi HA, Kurfess TR (2001) Force control grinding of gamma titanium aluminide. Int Journal of Machine Tools & Manufacture 43:185–191
- Furness RJ, Tsao TC, Rankin JS, Muth MJ, Manes KW (1999) Torque control for a form tool drilling operation. IEEE Trans on Control Systems Technology 7(1):22–30
- Arvajeh T, Ismail F (2006) Machining stability in high speed drilling—part 2: time domain simulation of a bending–torsional model and experimental validations. International Journal of Machine Tools & Manufacture 46:1573–1581
- Kim JB, Lee SJ, Park YP (1994) Stable and efficient drilling process by active control of the thrust force. Mech Syst Signal Process 8(5):585–595
- Haber RE, Gajate A, Liang SY, Haber RH, del Toro RM (2011) An optimal fuzzy controller for a high-performance drilling process implementation over and industrial network. International Journal of Innovative Computing, Information and Control 7(3):1481– 1498
- Sheng Y, Tomizuka M (2006) Intelligent modeling of thrust force in drilling process. Journal of Dynamic Systems Measurement and Control-Transactions of the ASME 128(4):846–855
- Xiaoli L, Yingxue Y, Zhejun Y (1997) On-line tool condition monitoring system with wavelet fuzzy neural network. J Intell Manuf 8: 271–276
- 11. DeHart A., Murphy D (2004) "Machine shopping: how to become a better-informed machine tool consumer,". [Online]. Available: http://americanmachinist.com/machining-cutting/machine-shopping.

- Wojciechowski S, Chwalczuk T, Twardowski P, Krolczyk G (2015) Modeling of cutter displacements during ball end milling of inclined surfaces. Archives of Civil and Mechanical Engineering 15(4):798–805
- Hashimoto F, Lahoti GD, Miyashita M (1998) Safe operations and friction characteristics of regulation wheel in centerless grinding. Annals of the CIRP 47(1):281–286
- Hashimoto F, Zhou SS, Lahoti GD, Miyashita M (2000) Stability diagram for chatter free centerless grinding and its application in machine development. Annals of the CIRP 49(1):225–230
- Hahn RS (1954) On the theory of regenerative chatter in precisiongrinding operations. Transactions of the ASME:593–597
- Hahn RS (1959) Vibrations of flexible precision grinding spindles. ASME Journal of Engineering for Industry 81:201
- Hahn RS (1963) Grinding chatter: causes and cures. Tool Manufacturing Engineering 51:74
- Gurney JP (1962) General analysis of two degrees of freedom instability in machine tools. J Mech Eng Sci 4:53
- Rowe WB, Koenigsberger F (1965) The work-regenerative effect in centerless grinding. International Journal of Machine Tool Design Research 4:175–187
- 21. Mallet SG (1998) A wavelet tour of signal processing. Academic Press, Burlington
- Griffin J, Chen X (2014) Real-time fuzzy-clustering and CART rules classification of the characteristics of emitted acoustic emission during horizontal single-grit scratch tests. Int J Adv Manuf Technol 1–22
- Griffin J, Chen X (2009) Multiple classifications of the acoustic emission signals extracted during burn and chatter anomalies using genetic programming. Int J Adv Manuf Technol 45(11–12):1152– 1168