Int J Adv Manuf Technol (2017) 93:811–823
DOI 10.1007/s00170-017-0320-3

ORIGINAL ARTICLE

Multiple classification of the force and acceleration signals extracted during multiple machine processes: part 1 intelligent classification from an anomaly perspective

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Received: 19 September 2016 / Accepted: 1 March 2017 / Published online: 29 May 2017

Abstract This paper is the first in a two-part work, where the investigation into the characteristics of multiple machine processes is made in order to accurately control them via the frequently used machine centre platform. The two machining processes under investigation are grinding and hole making: for grinding anomalies, grinding burn and chatter and for hole making, drilling, increased tool wear and onset of drill tool malfunction, which is also significant to severe scoring and material dragging. Most researchers usually report on one machining process as opposed to multiple which is less consistent with automated flexible systems where more than one machining process must be catered for. For efficient monitoring of automated multiple manufacturing processes, any unwanted anomalies should be identified and dealt with in a prompt and seamless manner. This first part provides two experimental set-ups (same set-up with tool interchange) to obtain signal signatures for both grinding and drilling phenomena (using the same material). Here, an approach based on neural networks and CARTs is used to reliably detect anomalies for both processes using a single acquisition path, opening the door for control implementation.

Keywords Burn · Chatter · Force · Accelerations · Drilling · Tool malfunction · Grinding · CART · Neural network · STFT

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1 Introduction

Current literature does not have much information of multiple intelligence for multiple machine processes which is what this paper focuses on. Why there is not much literature is due to the fact that accurately controlling multiple processes through one AI and a single platform set-up, it is considered almost impossible when summarising the associated degrees of freedom in potential sources of error [1]. The modular detection of different phenomena specific to a machining process is therefore very important when carrying out multiple process monitoring. For instance, with respect to grinding, there are many different types of grinding phenomena ranging from cutting, ploughing, rubbing, cracking, burn and chattering. Another process maybe that of drilling or milling where each has their associated sources of error/anomaly detection (is it the wear in phase or on-set of tool malfunction for example). Some of the research discussed here will investigate the identification of grinding burn, chattering and detection of surface anomalies through a single channel by means of sensor fusion.

Grinding burn can be considered as a key unwanted phenomenon when grinding aerospace materials such as Inconnel 718 [2]). This is due to the uneven re-hardening of a material giving brittle characteristics as well as the increased possibility of micro cracks. If burn or even slight burn occurs during the manufacturing process of safety critical components, e.g. turbine engine blade or disk, then that unit would have to be either re-melted and scrapped or further machined if within surface integrity limits. This action is due to the aerospace requirements being very stringent when manufacturing commercial engine parts. For instance, if they fail due to a hair line crack caused by slight burn [3], this could cause catastrophic results and ultimately result in death. By extracting signals from each individual process, it is possible to control output flow allowing optimisation for each machining process. Rule optimisation using heuristics seen in other areas of investigation where different individual elements of the process can be optimised. Such accumulation of element optimisation can give overall reductions on lead times [4] which is another significant facet for manufacturing and a similar approach is applied here albeit to control unwanted anomalies. This is one way of identifying control and another is forming intelligence from statistics statistical process control.

Grinding burn occurs from the increased grinding temperature when abrasive grits come into contact with workpiece material. This heat, however, cannot dissipate quickly due to too much heat generated during material being removed or there is not enough coolant present. There are also other factors, such as a worn grinding wheel due to loading, which when not dressed appropriately promotes burn [2, 5].

Chattering or chatter, however, is another grinding machining phenomenon that needs to be identified and stopped. Chatter produces surface waviness and is caused by excitation at the normal vibration frequencies of the machining system. Chatter can be identified through force, acceleration, power and acoustic emission signal extraction [6, 7]. In the case of surface roughness, recent developments have allowed to get significant results in progressing towards non-contact methods for estimating surface roughness of workpieces after grinding by the simultaneous use of time series analysis and wavelet transforms [8]. The use of such high performance and low-cost techniques into integrated multi-process control systems shows promise in the future for making more robust systems for the detection of unwanted phenomena. Other works [9] currently focus on the use of optical methods for the characterisation of abrasive tools, instead of using contact methods, which drives a move away from more invasive techniques, effectively enabling better implementation into one machining platforms. Efforts using image processing technologies [10] and acoustic emission sensors [11] during manufacture are also solid evidence of this tendency.

Other moves towards more precise non-contact manufacturing practices come from making sure the manufacturing tools are properly taken care of and through the use of new technologies in tool maintenance. An example of such efforts is the ones by Zhou et al. [12], which has focused in augmenting the quality of laser profiling for dressing of grinding wheels by the variation of power to the laser, which shows high promise for alternatives to diamond dressing.

The motivation of this paper surges from the need of striving towards autonomous manufacturing platforms to be able to achieve 'lights out manufacturing', where minimal supervision is needed. One of the key considerations here is the predictability of the processes, because it is necessary to consider any portion of the process that requires human intervention, and replace it. 'We document the complete machining process of a part over a 24 to 40-hour time period, sometimes longer if necessary', [13], this is an example of the efforts of the industry to replicate human work, considering all possibilities for a predictable process.

Higher complexity parts and larger production runs however will require more formalised plans to achieve the desired 'lights out' results. To automate these predictable activities, it's essential to have software driven approach. In this sense, closed loop systems that monitor critical dimensions of the workpiece and adjust tool compensation automatically have become mainstays for lights out manufacturing control.

Tool management, aside from a predictable machining process, is inarguably the most important aspect of a successful lights out operation. 'Once behaviour of your perishable tooling is known and the exact variables of tool wear have been properly defined, it is recommended to set up a job and running it unattended with small incremental adjustments' [13]. 'This exercise reveals what the tool wear and part growth are over time. We call this phase 'dimming the lights' before you shut them off'.

Other important aspects of a successful lights out operation involve coolant and chip management, plus parts and material handling. 'These might seem like elementary, obvious things to consider, but are often the areas where people new to running unattended are prone to trip up', [13].

In this paper, the research looks at the results gained from two trials, namely investigating grinding chatter and burn (with the same commercial machining rates and aerospace material: Inconnel 718). Both signals obtained from the two separate trials provide signals that are difficult to distinguish in terms of grinding phenomena, especially segregating both chatter and burn.

The second part of this paper in controlling multi-machine processes investigates the control of hole making as a secondary machine focus. A similar control regime is proposed as seen in the control against grinding anomalies (same measured signals and workpiece material/set-up), albeit the model's control of drilling tool malfunctions is distinctly different (see part 2 Section 3.2 of this work). There are various research investigations in control of hole-making processes for instance; Ulsoy and Koren [14] discuss multi-process control, where the fundamentals are based around supervisory, process and servo control. This is where the machine is controlled by position and velocity; the process is controlled by measuring force and wear and finally, the product is formed from controlling dimensions and surface quality. It was discussed that future systems would require not three but many different types of control integrated within a system and driven as individual entities. A key requirement needed for these future configurable systems is the need for integrated sensing capabilities. This is certainly the path where multi-process configurable intelligent machines are heading. The work presented here looks much deeper into how such possibilities can be carried out measuring surface anomalies of both grinding and drilling. There is no need to distinguish 'which process is which' as the CNC has this integrated ability, instead the different control extensions should be carried out for each individual machining process.

By controlling key parameters within the drilling process such as torque, feed and spindle speeds, it is possible to ensure the part is machined to required quality as well as being able to control against tool malfunction (associated to machine stoppage). From the trials carried out, the supervisory control of the drilling process aligns the theoretical, with the applied, where such ideas are central to the work delivered here; however, the work here investigates a real possibility for machine-embedded integration. For example, the proposed Simulink model displays how such an embedded control regime could be implemented for industrial exploitation.

The multiple classification system proposed here gives an approach to a generic monitoring system ultimately used in control feedback regime. This is indicative to both workpiece chatter and burn, respectively, in terms of identifying a progressively roughening surface finish or a progressively deteriorating grinding wheel due to wear. This level of understanding of grinding phenomena is what is required for a reactive successful monitoring system [15]. Without useful extraction techniques and observable results (in terms of actual obtained anomalous phenomena), the data is useless for the presentation of a robust, general characterisation.

In addressing these shortfalls, Griffin and Chen [16] used neural networks (NNs) to monitor acoustic extracted signals correlated to different grinding phenomena such as cutting, ploughing and rubbing which essentially leads to more efficient grinding. Such NN paradigms can be used for correlating signals of force with different abusive conditions. This technique, however, might be inaccurate when applied to multiple output criteria. In addition, NNs, as a classifier, suffers in terms of multiple output classification; this is concerning modelling many different cutting conditions/machining processes. Other classifying techniques such as GP are more versatile to this and provide different rules that are found individually with concentrated demarcation classifiers and then merged together via a divide and conquer approach to provide robust complex classifier technologies for many different conditions/machining processes (Griffin and Chen, Multiple Classifications of the Acoustic Emission SIgnals extracted during burn and chatter anomalies using genetic programming [5]).

Machine learning techniques have played a vital role in assisting machine process monitoring. Of the many techniques applied to monitoring, NNs are considered the most extensive [17]; however, in the last decade, a number of different classifiers with a greater emphasis towards evolutionary computing techniques have emerged as successors to this type of classifier. Where a hybrid classifier distinguished patterns [18], in this case, no/burn or no/chatter.

In Section 4 of this work, a more detailed discussion can be found introducing intelligent control algorithms, namely Classification and Regression Trees (CART) and NN. Such classification technologies were used in this work due to the characteristics where CART gives easily transferable rules for embedment and NN are appropriate for large signal data analysis.

Currently there is very little or no work looking at multiple anomalies for multiple machine processes for a single material in a single fixture, which is what this two-part works report on. Very similar to grinding, the force, accelerations, temperature, power and AE can also be used to monitor the onset of drilling tool failure (scoring, dragging and tool malfunction); however, the work presented here focuses on only the measured force and accelerations (much easier to integrate and more susceptible to trend rather than sporadic changes).

The main investigation objectives of this paper are as follows:

- Characterise grinding chatter and burn from normal grinding conditions.
- Analyse grinding chatter and burn signals for Inconnel 718 aerospace material.
- Characterise abusive drilling conditions.
- Analyse different abusive drilling conditions for the same Inconnel 718 aerospace material as grinding (satisfying multiple machining processes).
- Produce an intelligent grinding signal monitoring technology for multiple process control using the same extracted force and acceleration signals.
- Produce an intelligent hole-making signal monitoring technology for multiple process control using the same force and acceleration signals.

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 for future, flexible manufacturing systems. The rest of the paper is organised into the following sections: Section 2 Experimental set-up, Section 3 Force and accelerations identification, Section 4 Technologies for intelligent control of multiple processes, Section 5 Results for intelligent control of multiple processes, and Section 6 Conclusions.

2 Experimental set-up

For setting up the grinding burn experiment, the following set-up was applied (see Fig. 1), and providing increasing depth of cuts (DOCs), it was possible to gain burn phenomenon with increasing intensities (dressing ratios implemented between each cut). The chatter experiment would require the same set-up; however, the DOC would be fixed to 1 mm DOCs

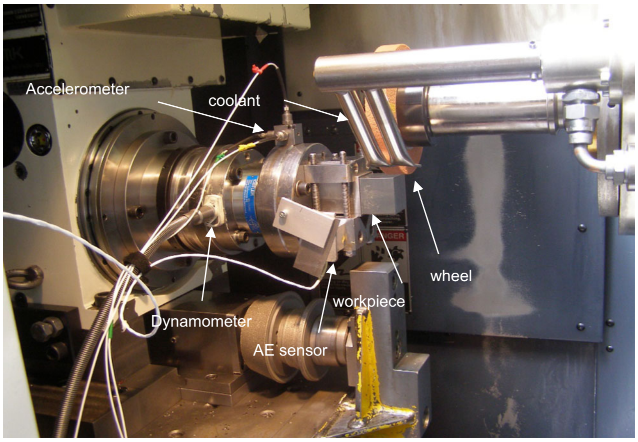


Fig. 1 A55 machine centre set-up for chatter experiment (same machine was used for the drilling trials)

and to increase the chattering phenomenon grinding dressing ratios would be decreased/suppressed to allow material pickup and force increased chattering vibrations. The burn and chatter phenomena would then be recorded by force dynamometer, accelerometer, power meter and with correlated recordings of workpiece/grinding wheel image. The phenomenon would be measured in terms of where it occurred on the workpeice. The grinding cut signal obtained by each sensor would then be stripped from the total recorded stream and then measured to correlate the physical burn or chatter with the digitised signal source. This is fundamental to the understanding of different grinding phenomena.

As shown in Fig. 1, the set-up of the grinding process monitoring consisted of the following: a Makino A55 machine centre, two Digital Acquistion Cards (DACs) being housed on one computer platform and a Kistler dynamometer and accelerometer measurement system that would be situated next to the workpiece to take full advantage of material vibrations.

For the grinding burn phenomenon trials, the following parameters in Table 1 were used (increased DOC without coolant promotes the burn phenomenon). Table 2 displays the grinding conditions used for the chatter phenomenon trials. Chatter would be achieved from the increasing levels of wheel loading from several consecutive grinding passes with the conditions presented in Table 2. Only pre-trial wheel dressing was carried out for each chatter trial (three trials carried out for burn and chatter identification). Table 3 gives the drilling trials conditions for the same machine set-up.

For both trials (chatter and burn), the machine was set-up with a fixed workpiece and grinding wheel attached to the spindle. Instrumentation sensors were initially checked for reliability and correct amplifier sensitivities; this was to ensure the signal intensities would not saturate and render the results unusable. The wheel diameter was measured followed by the dressing of the wheel. Grinding conditions were adjusted as required for the experiment (in the burn case increasing depth of cut with no lubricant in order to promote burn, with chatter both coolant and increased wheel speed was adapted). The extracted signals would then be logged and saved to files. Image data regarding wheel loading and workpiece surface integrity were taken for chatter tests and every third cut for burn tests using a microscope image (×25 magnification) after each grinding cut. The sample width and thickness would be measured and noted along with observations of the temper colour change signifying the physical burn characteristics. These steps would be repeated for successive depth of cuts. For validity of the experiments, triplication of results would be carried out in a sequential manner. A similar strategy would be carried out for the chatter phenomenon experiments; however, more scrutiny would be placed on surface roughness (Ra), wheel and actual depth of cut measurements as well as chatter audible sound. All the obtained information from the various sensory systems would be processed and summarised for automated classification.

With all these signals processed, concatenated into an understandable format they are then trained and tested against the classifier system. The method here would employ a test of

Table 1 Grinding conditions for burn trials

Grinding parameter	Condition
Depth of cut	0.1–0.6 and 1 mm
Feed rate	1000 mm/S
Wheel speed	35 m/S
Wheel diameter	134.94 mm
Wheel material	Al_2O_3
Workpiece material	Inconnel 718
Coolant delivery	None

Table 2 Grinding conditions for chatter experiment

Grinding parameter	Condition
Depth of cut	1 mm
Feed rate	1000 mm/S
Wheel speed	55 m/S
Initial wheel diameter	138 mm
Wheel material	Al_2O_3
Workpiece material	Inconnel 718
Coolant delivery	70 bar Hocut 3380

Table 3 Drilling conditions for tool malfunction experiment

Drilling parameter	Condition
Depth of cut	12 mm
Diameter	8 mm
Feed rate	Tool 1:1.5×, 2: 1×, 3: 1×
Wheel speed	Tool 1: 1.5×, 2: 1.3×, 3: 1×
Workpiece material	Inconnel 718
Coolant delivery	70 bar Hocut 3380

several cases seen by the classifier and several cases not seen by the classifier. This technique would provide sufficient results to decide whether the classifier had generalised the difficult to distinguish phenomena. This would give the user an idea that the classifier can make generalised classifications as well as give higher confidence, in terms of repeatable results.

3 Force and accelerations identification

The following section displays the signal results for both machining processes: grinding and hole making.

3.1 Chatter and burn grinding trials

The force slightly decreases with greater harmonics in the case of chatter when compared with no chatter. The power is somewhat similar and less sensitive to change; however, the accelerations are greater with more frequency components in the chatter case than when compared with the no chatter case (see Fig. 5). The objective here is to take that data and form an expert system distinguishing chatter from no chatter. More in depth data relating to the experimental set-up and measurements can be found in previous work [5]); however, Fig. 2 displays the different DOC representative of different levels of experienced burn when grinding Inconnel 718 aerospace alloy. Two experiments were carried out for repeatability. Figure 3 displays both the set-up post-cut and the wheel material loading characteristic of severe burn. Figure 4 displays the recorded surface roughness along with the grinding wheel diameters all significant of the chatter anomaly, where each trial is separated by vertical lines. Triplication was necessary for verification of contradicting phenomena where the force drops during the chatter phenomenon; this was consistent for all three trials.

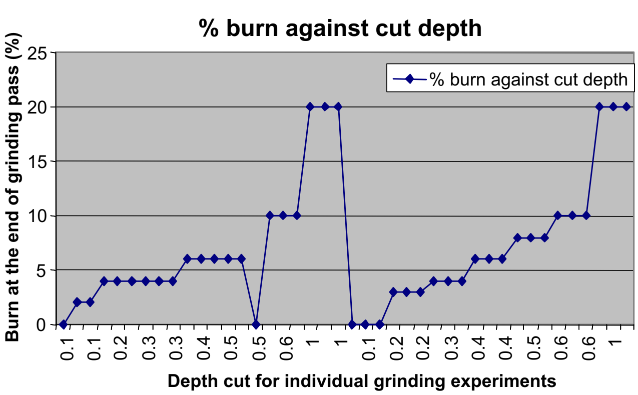


Fig. 2 Displays the burn cases for grinding tests. *Percentage* represents the estimated portion of the surface burned after the cut. Grinding conditions: machine: Makino A55, wheel: Al_2O_3, workpiece: Inconnel 718, burn trials A_p 0.1 mm ➔ 0.6 and 1 mm, DRY down grinding: $V_S = 35$ m/S, $V_W = 1000$ mm/min

Looking at Fig. 6 with the burn case, the forces are much higher, by a factor of approximately 2, than the no burn case both in the case of the force normal to the workpiece surface (Fx) and the one along the cutting direction (Fy), while the salient features have similar form. Naturally, a greater amount of energy enters the workpiece when under the burn condition, as there is more material friction and resistance as a by-product of these cutting conditions.

3.2 Hole-making tool malfunction trials

For the case of drilling trials, three different tools were compared while drilling 120 holes until failure occurred to detect the onset of wear and other cutting anomalies.

Figure 7 displays different internal hole scoring; this is where the drilling tool exists the hole abusively (left) or controlled (right). Such abusive conditions are known as drilling anomalies and occur from excessive forces and vibration from excessive loading and poor coolant delivery. For instance, abusive conditions lead to unwanted residual stresses, cracks and overall poor tolerances.

Tool 1is significant of signal change from the datum (first hole) to the malfunctioning 20th hole. The challenge here for intelligent classifiers can be due to the ‘wearing-in’ phase of a tool where all new tools experience a slight abrupt increase in monitored signatures. The key recognition feature is based around the trajectory of the abrupt change which can be significant to a drilling tool under abusive loading conditions. Looking at Fig. 8, this gives the datum (first hole), followed by a wearing in period (hole 40) and an abrupt loading case significant to high speeds and poor coolant delivery (hole 60). If the tool had focused sufficient coolant delivery and the loadings were kept constant and within tool operating limits, the signals gained for hole 40 would remain similar for the duration of the required 120 holes. These signals along with accelerations (see Fig. 9) give good discriminators when distinguishing between a good, healthy tool and a tool that is either going to malfunction or provide internal surface issues such as scoring, micro cracks, plucking or large burrs. Figures 8 and 9 were chosen as the signals were very similar to tool 1; however, the changes were more abrupt later on due to insufficient coolant supply.

4 Technologies for intelligent control of multiple processes

4.1 CART rule-based system for classifying multiple machining anomalies

The tree viewer classifier uses the CART algorithm to carry out classification; CART is particularly useful in segregating n-dimensional data sets and produces transparent, easily

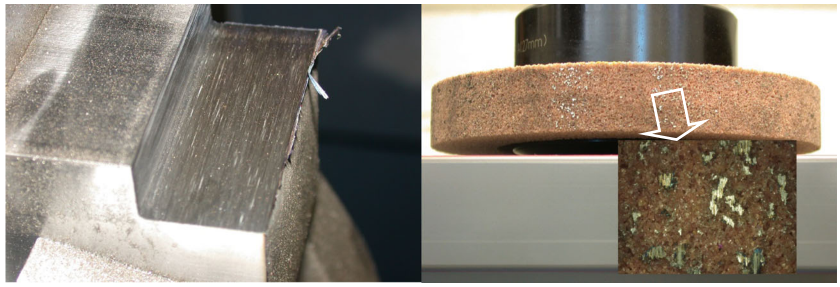


Fig. 3 *Left*, Inconnel 718 burn after dry cut 1 mm (A_p) and *right*, material loading on the Al_3O_2 wheel as well as microscopic image of material build-up

readable set of classification rules. There are other techniques which are similar to optimised fuzzy clustering such as genetic programming (GP) as seen in work discussed by Griffin and Chen [5]); however, when faced with n-dimensional data with no pre-processing reduction, other techniques are more favourable. Moreover, GP with n-dimensional reduction techniques affords a very powerful classification system; however, on its own with n-dimensions, a different technique needs to be pursued. CART however is a method of classification similar to fuzzy clustering with the added facet of producing more transparent rules. As mentioned before, CART is also suitable for n-dimensional datasets which is why it is presented here and by using pre-processing techniques in real-time are unsuitable based on the increase in computational complexity which impacts on real-time processing.

CART builds classification and regression trees for predicting continuous dependent variables (regression) and categorical predictor variables (classification) [19]. It achieves its functionality by recursively splitting the feature space into sets of non-overlapping regions (rectangles in the case of continuous features; subsets of values, in the case of categorical features) and finally by predicting the most likely value of the dependent variable within each region. By generating a binary tree through recursive partitioning, it splits the data into sub-nodes based on the minimisation of a heterogeneity criterion computed at the resulting sub-nodes. With the CART algorithm, the tree is forwardly propagated (using forward stepwise regression) for best purity of node split. The best node split becomes the chosen value of partition (see Eq. 1).

A good splitting criterion is the following:

PRE = $\emptyset(s,t)$.

Where PRE is the minimum production reduction error and s is the split at any node t. The best purity measure looks at the best unique minimal classification where impure would be to have many unnecessary classes. For the CART algorithm the accuracy percentage of classification is used as the best purity measure.

Misclassification error:

$$Q_m = \frac{1}{N_m} \sum_{x_i \in R^m} (y_i \neq k(m)) = 1 - \hat{P}_{mk(m)} \tag{1}$$

where y_i is the output of the individual under test and $k(m)$ is the class category under test.

This method of classification is chosen because the tree fitting methods are actually closely related to cluster analysis [20]. This is where each node can be thought of as a cluster of objects, or cases, that are split by further branches in the tree. Note that the top node covers the whole sample amount and each remaining node contains a sub-amount of the original sample and so on as the split levels increase.

In the example displayed by Fig. 10, the total data set can be seen from species at the top node of the tree classifier. The condition of petal 'len' is the first variable and if species are less than 3.00, then the data class category will tend towards the right-hand side split (example: displaying the red line [left

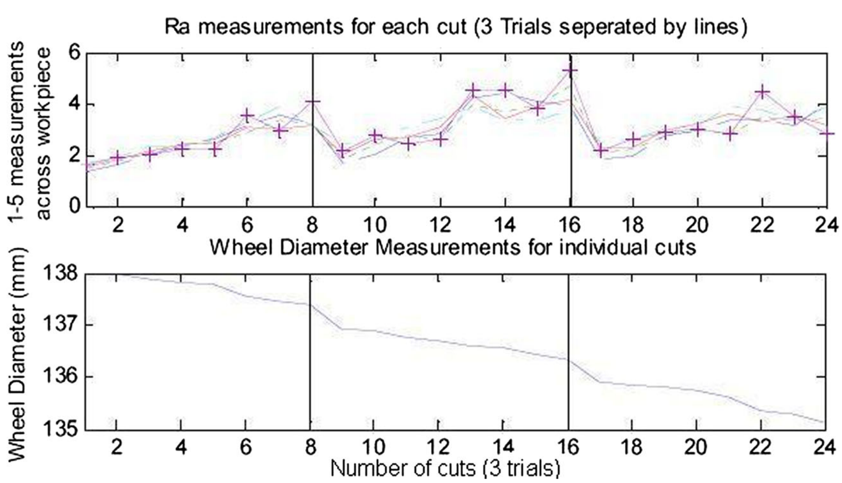


Fig. 4 Displays the relationship roughness (μm), wheel wear and cut lengths for chatter experiment (mm)

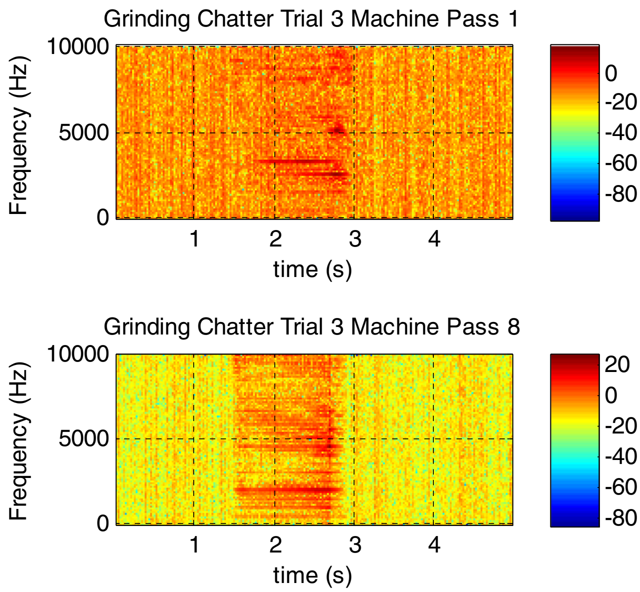


Fig. 5 Displays the STFT of the first (no chatter) and final pass (chatter) of the third test displaying more salient frequency bands experienced during the chatter condition (*z* axis accelerations). Machine: Makino A55, grinding wheel: Al_2O_3, workpiece: Inconnel 718, wheel width 15 mm, chatter trials A_p 1 mm, coolant on & down grinding: V_S = 55 m/S, V_W = 1000 mm/min

most line] class). If however the petal 'len' is greater or equal to 3.00, then the left-hand branch is taken, splitting the remaining part of the total data set. Lastly, the last branch has a second condition for a second parameter providing both further splits right and left. If petal 'wid' is less than 1.30, then the left hand branch is taken otherwise, the right-hand branch. This is a simple example of flower stork dimensions classification but displays the functionality behind the CART classification algorithm.

A classification tree represents a set of nested logical if-then conditions (similar to a rule-based system) on the values of the feature variables that allows the prediction of the value for the dependent categorical variable based on the observed values of the feature variables. A regression tree also represents a set of nested logical if-then conditions on the feature variables, but these are used instead to predict the value of a continuous response variable.

CART can handle missing values by imputing such values in obtaining the mean over the complete observations. The model can be tested on a separately specified test set. Additionally, the model can be saved and used subsequently on additional test sets.

Some points for discussion on best tree representations are as follows:

- A very large tree may over fit the data.
- A small tree might not capture the important structure.

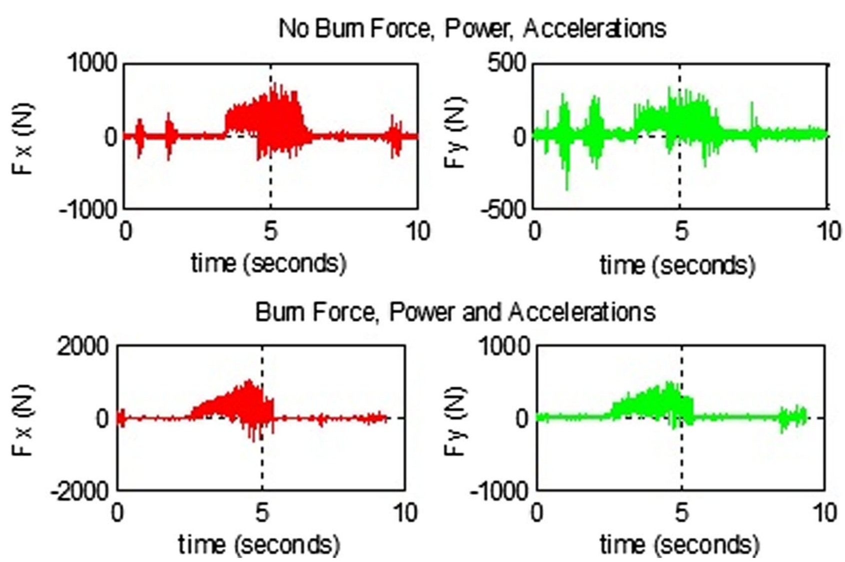
Therefore, there is trade-off consideration for the best tree when thinking of the overall size:

- The optimal tree size should be adaptively chosen from the data provided.
- Different stopping criteria's can give different results such as an impurity threshold is reached and the branching and splitting is halted or a specified minimum of branch level is achieved, so branching and splitting is halted at this point.
- Think of a pruning strategy that does not impact on the overall tree classification accuracy.

4.1.1 The advantages of tree-based methods

Tree-based classifiers can cater for both categorical and ordered variables in a simple and natural way. Automated stepwise variable selection with built in complexity reduction

Fig. 6 Inconnel 718 no burn/burn force measurements. Grinding conditions: machine: Makino A55, wheel: Al_2O_3, workpiece: Inconnel 718, burn trials A_p 0.1 mm ➔ 0.6 and 1 mm, dry down grinding: V_S = 35 m/S, V_W = 1000 mm/min



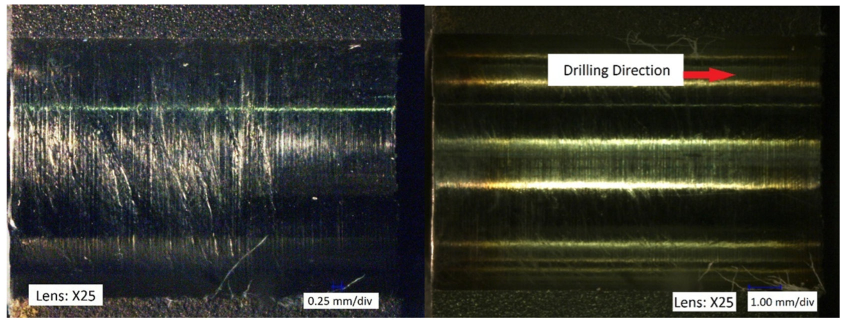


Fig. 7 Differences between a hole with marked internal scoring (*left*: tool 3) and acceptable scoring (*right*: tool 2)

ensures powerful and compact rules are found. CART provides estimates for query samples based on the misclassification rate which gives the technique further confidence in its ability to accurately classify. Tree-based methods are invariant under all monotone transformations of the individual ordered variables. Such a paradigm is also robust to outliers and misclassified points based on the training set. Finally, one of the important reasons for being used here is its ability to give easy to interpret outputs.

4.1.2 Limitations of trees

One important consideration is reference to the high variance of output based on its hierarchical nature to classify. A small change in data may result in different splits, thus making such interpretations precautious. Errors made from the top node filter all the way down to the lower nodes. Such limitations have been reduced based on bagging averages and using random forest techniques. All tests carried out using this technique were verified against test and verification unseen data sets. With high classifications, added confidence in terms of the accuracy to the obtained tree is achieved.

4.2 Neural network classifiers

A large number of researchers have reported the application of using neural network (NN) models for the classification of phenomena of interest when applied to tool condition monitoring ([21, 22]. A feed-forward neural network model was used with the back-propagation learning strategy to provide the segregation of data. Commonly, NNs are used for pattern recognition in image analysis or sound waves in signal analysis. The NN consists of a complex interconnection of units which are otherwise known as nodes or neurons. The general layout for a NN consists of a set of neuron layers connected together through complex connections; this layout and features are known as the network architecture.

A multi-layer NN is required due to the more complex data presented by STFT signal processing techniques. This type of data is not only non-linear but also n-dimensional. The basic logic function network classifiers (Such as OR, NOT and AND) use a linear data separation approach; however, with the separation of much larger data sets, there is need for a more dynamic learning system that takes all the information into consideration and maps the data in both parallel and gradient descent segregation fashion such as that seen by the back-

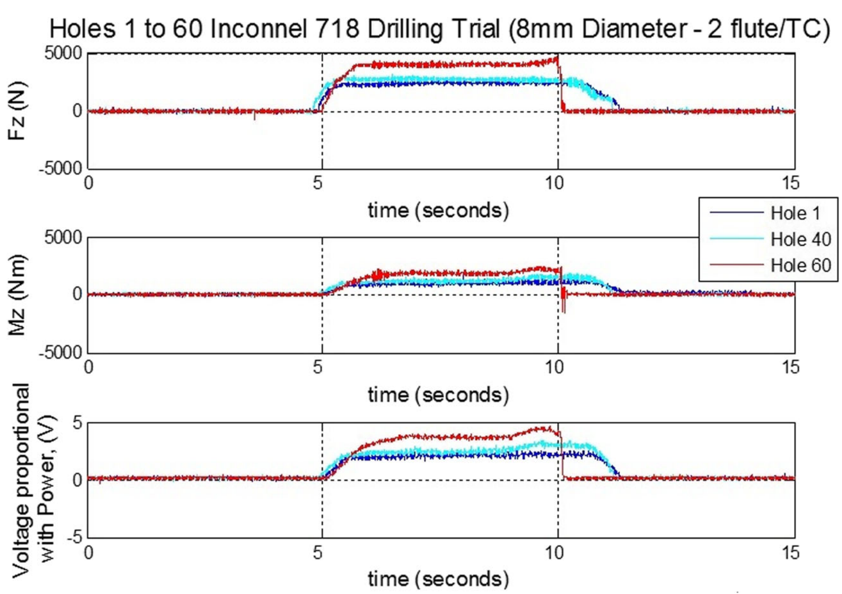


Fig. 8 Displays the change in signals from drilling initial hole to the 60th hole where failure occurred (tool 3)

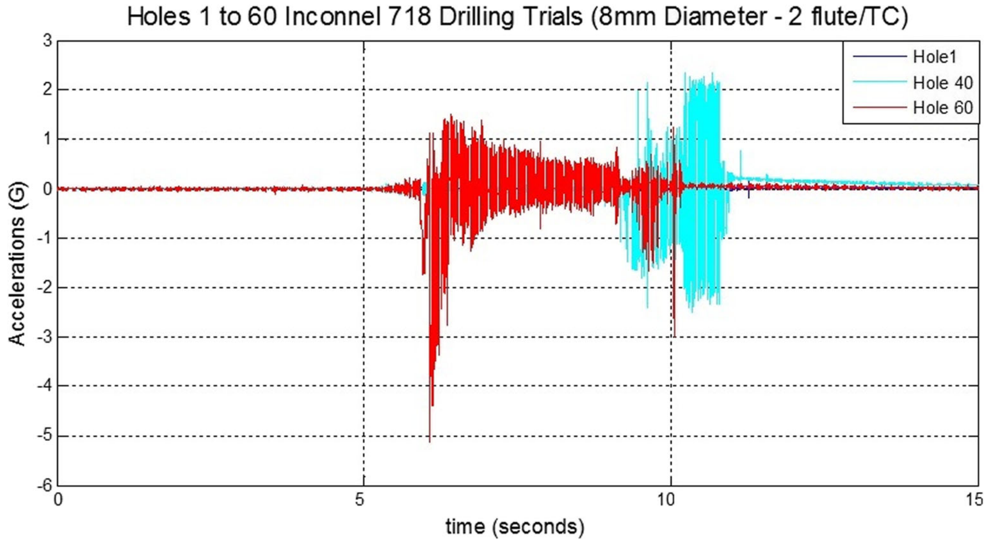


Fig. 9 Displayed are the corresponding accelerations for the signals displayed in Fig. 12. Again, hole 60 was imminent of tool failure (tool 3)

propagation feed-forward network. A multi-layer perceptron (MLP) utilising the back-propagation learning rule is presented in Fig. 11 for illustration purposes.

As displayed in Fig. 11, each of the inputs P_1 to P_4 are multiplied by a changing weight function and are associated to a target vector, in this example, a_1 to a_2, respectively. This is called the associations of input-output pairs and provides the supervised training data (test and verification data set have both data that has been seen by the network in training (supervised) and data that has not been seen (testing the generalisation of the network)). Each neuron has a summation function which sums up the weighted (for example, $w_{1,1}^{1}$ and $w_{1,2}^{1}$ to $w_{n,n}^{2}$ reference Fig. 11) and input bias (bias input variable) connections. The transfer function (for non-linear problems a differential transfer function, such as Tan-sigmoid is used) is required to map the non-linear input-output relations which are obtained for each neuron and updated in an iterative fashion towards the desired target set. Back-propagation is so called as the weights are updated from the error between the actual output and the desired output which in short is from the back to the front. This method segregates the different classes based on the supervised training data given to the NN. The summation of weights and bias values are multiplied by a differential transfer function to give a neuron output.

The output of each neuron is a function of its inputs. Specifically, output of the j^{th} neuron is with respect to any layer and is described by the following equations:

$$U_j = \sum(Pi \times w_{ij}) \tag{2}$$

$$a_i = F(U_j + t_j) \tag{3}$$

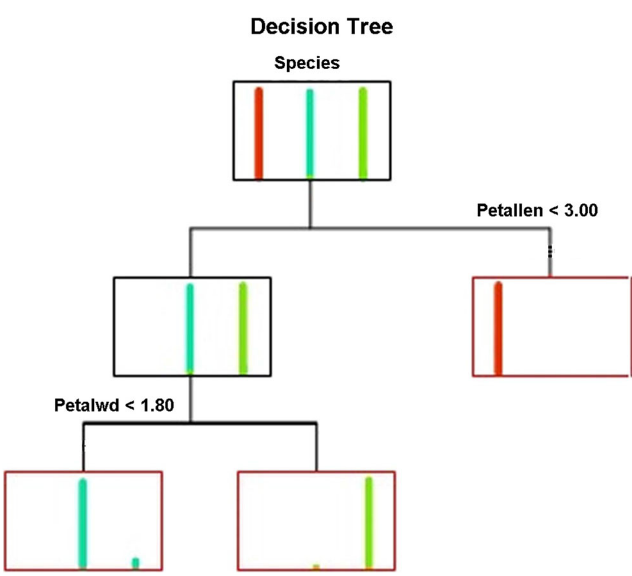


Fig. 10 CART example of classification rules

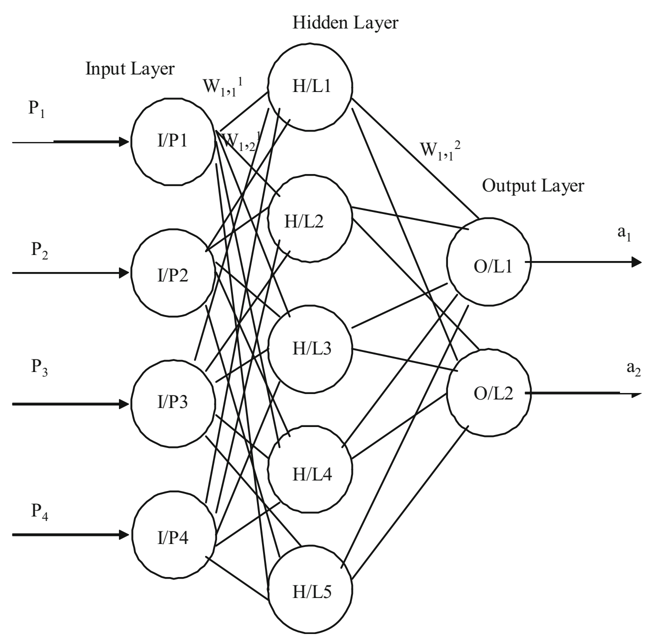


Fig. 11 A four-input NN with one hidden layer

For every neuron, j, in a layer, each of the i inputs, X_i to that layer is multiplied by a previously established weight, w_{ij}. These are all summed together, resulting in the internal value of the operation, U_j. This value is then biased by a previously established threshold value t_j and sent through an activation function, F (non-linear or linear), giving the NN output, a_i.

Equation (4) describes the output error obtained from each neuron.

$$\mathrm{ME} = \frac{1}{\Omega}\sum_{i=1}^{\Omega}(t_i - a_i)^2 \tag{4}$$

where ME is the mean squared error, a_i (a_1 and a_2 in the example displayed in Fig. 11) is the output of the network corresponding to i^{th} input (P_1 to P_4 in the given example). The error term of network is given from $(t_i - a_i)$ where t_i is the target vector or the desired value for given input vectors P_1 to P_4. The squared term is used to transpose the matrix to ensure both matrices are multiplied together to get a sum squared error output. The error function can be applied to the NN in a batch training fashion at the end of data presentation or sequentially after each input-output pair.

Another form of the CART Decision tree is provided by listing below (for burn trials classification):

```
1  if x85<-0.00961471 then node 2 elseif x85>=-0.00961471 then node 3 else 2

2  if x73<-0.0135652 then node 4 elseif x73>=-0.0135652 then node 5 else 2

3  if x67<0.0154098 then node 6 elseif x67>=0.0154098 then node 7 else 1

4  class = 1

5  class = 2

6  if x58<-0.0088414 then node 8 elseif x58>=-0.0088414 then node 9 else 1

7  class = 2

8  if x4<0.0133863 then node 10 elseif x4>=0.0133863 then node 11 else 1

9  if x79<-0.00499137 then node 12 elseif x79>=-0.00499137 then node 13 else 0

10  class = 1

11  class = 0

12  if x68<0.00263945 then node 14 elseif x68>=0.00263945 then node 15 else 2

13  if x79<0.00096374 then node 16 elseif x79>=0.00096374 then node 17 else 0

14  class = 2

15  class = 1

16  if x1<0.0113503 then node 18 elseif x1>=0.0113503 then node 19 else 0

17  if x44<-0.00112952 then node 20 elseif x44>=-0.00112952 then node 21 else 1

18  class = 0

19  class = 1

20  class = 1

21  class = 0
```

Fig. 12 CART rule output for burn classifications (*0* normal grinding, *1* slight burn and *2* burn)

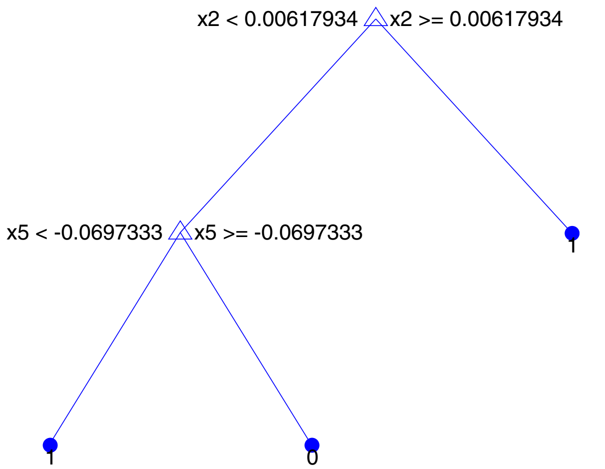


Fig. 13 CART rule output for chatter classifications (*0* normal grinding and *1* chatter condition)

For the back-propagation algorithm, the weight and bias update equations are as follows:

$$\Delta w_{ij}^{k} = -\alpha \frac{\partial \mathrm{ME}}{\partial w_{ij}^{k}} \tag{5}$$

$$\Delta b_{i}^{k} = -\alpha \frac{\partial \mathrm{ME}}{\partial b_{i}^{k}} \tag{6}$$

where α is the learning rate, which has a trade-off in value to ensure it is small enough to gain a true convergence but large enough to separate the data space in adequate time. Equations 5 and 6 are iteratively changed across the network along with other functions to provide learning sensitivity. This process of weight and input, and error calculation propagates through the NN to provide the segregation rules which separates the data according to class (target vector). The b is a bias term used to influence the training weights and for NN training.

5 Results for intelligent control of multiple processes

This section is broken up into two parts, the grinding anomalies (burn and chatter) and the drilling anomalies (on set of tool malfunction).

5.1 Grinding chatter and burn classifications

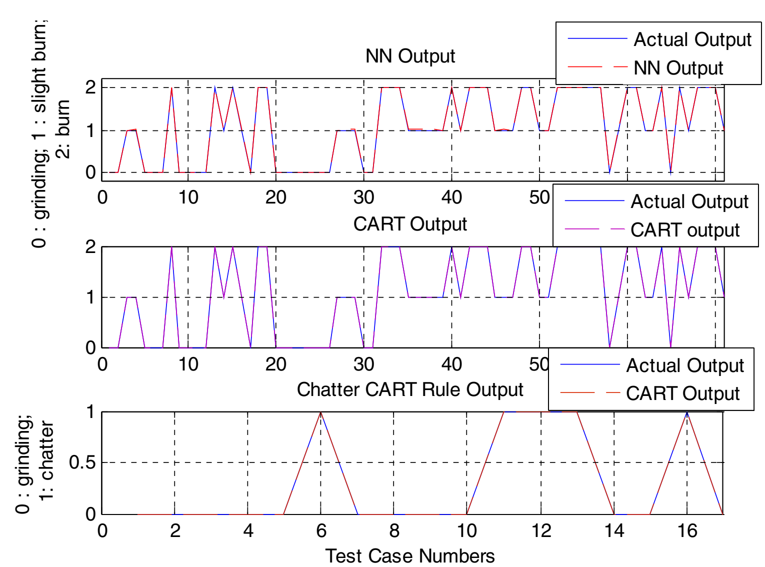
This sub-section displays the results gained from the intelligent control technologies. The first part looks at the individual outputs of CART and NN classifying burn and no burn cases (grinding). In addition, a small test set is displayed for classifying chatter against no chatter cases (grinding). This output test set is obtained from using the CART method.

5.1.1 CART and NN classifications of force and accelerations

Figures 12 and 13 display the CART rule outputs for burn and chatter, respectively. The less rules given, the more robust the classification process. This is why a small chatter test set was used with only the CART output as opposed to the burn test set which uses the combined weighted output intelligence of CART and NN. For the classifications, the decision tree is composed with rules based on the voltages read through the different acceleration acquisition channels. The variables used for classification are in the form of 'X_i', which represents the acceleration levels at i% of the current pass, e.g. ×85 is the acceleration level of the sampled down signal at 85% of the previous pass. This way sensor fusion is achieved to classify the underlying phenomenon in a lean way processing power-wise.

Figure 14 displays the intelligent control classification results for grinding anomalies. As can be seen, the classification results are very similar to the actual phenomena and therefore

Fig. 14 *Top*: burn classification NN Output, *middle*: burn classification CART output and *bottom*: chatter classification CART output for b & w versions the actual vs. the NN output are the same



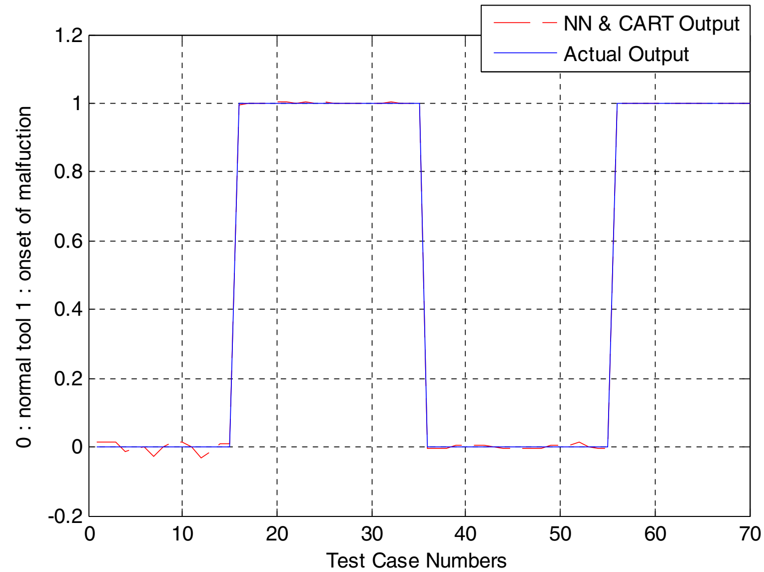


Fig. 15 Hole making combined CART and NN classifications for normal tool versus the onset of tool malfunction

gives a high confidence of use when transferred to the simulation environment (see part 2 of this work). The signals used for these classifications are based on time-frequency maps of the z axis accelerations. The time-frequency domain information (see Fig. 2 for time-frequency representation) was gained from the wavelet technique [23, 24]. The wavelet breaks up the frequency bands and gives salient representation for burn and no burn; hence, near complete classification accuracy is gained from the classifiers. The same method was employed for small chatter test set (see bottom of Fig. 14). Due to the gained high classification accuracies, it was possible to only use CART in the case of chatter signal demarcations.

5.2 Hole-making drill tool malfunction classifications

Looking at the results displayed in Section 5, it was established that by combining the intelligent control methods of CART and NN, a more comprehensive classification accuracy could be obtained. Due to this realisation, the methods for controlling against hole-making anomalies would use like these technologies. The way of implementing them was using a weighted representation of each classifier and adding them up to get a combined response, namely giving a ratio of 60% to CART output and 40% to NN outputs.

5.2.1 Combine CART and NN classifications for force and accelerations

The combined method of NN and CART again gives good account where (z axis) signals display the onset of tool anomalies/malfunctions (see Fig. 15). Such similarities allow the same control set-up where different databases can be used to signify different control regimes between grinding and hole-making. The simulation in part 2 of this work displays the grinding model when the CNC code calls grinding and the hole-making model when the CNC code calls drilling. As the overall models both utilise z axis accelerations as well as change in force level tendencies, automatic embedded system control could be represented by the same model with just the interchange between intelligent control data sets/rules (intelligent database).

For the force classifications, the simulation uses force data levels and trajectories to determine burn and chatter; however, the chatter is based on temporal information where a counter is used to determine a change in force due to cross coupling from the grinding chatter condition, and as such is used separately from the classifiers in part 2. This could be intelligently controlled as in the other cases using simulation mathematical functions are considered more robust. The same is also true of the force mappings for the onset of drilling tool malfunctions. Such coupling of intelligent control with traditional methods affords robust solutions which can handle more intelligence in a seamless manner: more than two machine processes each controlling against several machining anomalies.

6 Conclusions

For big manufacturers, such as aerospace companies manufacturing turbine discs, there is a need for multiple processes, such as drilling and grinding. These companies have very tight schedules based on the demand outweighing the supply capabilities. To ensure a move towards ‘lights out’ manufacturing, significant breakthroughs in robust control are necessary to allow one-machine platforms to perform all the work required. The work presented in the first of this two-part endeavour focused on multiple process anomaly detection through a sensor-fusion channel which is consistent with many precision machining tasks. This allows a single acquisition lane to control two processes, be it either grinding or drilling, when it is being carried out by a multi-tool machine. Depending on what task is being performed, the system can switch between one set of rules of detection to another, which is a simple switch that is provided by the CNC machine. Once an anomaly phenomenon has been detected through different sensing capabilities, it opens the door for implementation of the appropriate responses to handle each situation. The novelty showed here focuses in characterising more than one process for a given material, which allows a one-machine approach to its manufacturing using a dedicated multiple AI paradigm for control.

The results displayed in Section 5 display how the intelligent control methods can detect different conditions and through strong classification techniques can classify them in a robust and reliable manner. In the specific cases of drilling tool wear onset of failure, and grinding burn and chatter, the accurate classification of said phenomena was achieved reliably through the use of both CART and NN classifiers. In some cases, especially where force monitoring is being carried out, mathematical control functions could be applied in combination with intelligent control functions (see simulation in part 2).

It is important to note that the specific thresholds used for the detection of anomalies will be specific to the materials of both the tool and the workpiece, and as such their reliability for use in other interactions remains to be proven. The take-away from this work are both the CART rule and NN structures achieved, would be adaptable to different workpiece and tool materials, albeit requiring a calibration database. Within part 1, the intelligent control regimes accurately classify accelerations along the z axis for both grinding and drilling anomalies. Such that intelligent data control applications can be interchanged with only a single model used to connect the sensing inputs to control outputs.

Naturally, the transition into future work regarding this area involves the implementation of further manufacturing processes and anomaly detection capabilities into the models, to make the move towards robust and true one-machine manufacturing platforms.

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