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# FAILURE MODE ANALYSIS TO DEFINE PROCESS MONITORING SYSTEMS

The high costs of using skilled operators in production processes has built a demand for reduced manning, 'lights out machining' manufacture. Process monitoring systems have become a widely researched area in recent years since there is a need for intelligent systems to replace the manual intervention in existing processes. Furthermore, using modern sensors and signal processing techniques, monitoring systems can obtain more information about a process and therefore reduce costs further though maximised life of cutting tools, optimised cutting parameters and reduced scrap or re-work. With many application areas available, such as tool condition monitoring, chatter avoidance or feedback control of cutting parameters, it is not always apparent what the key aspects required by an intelligent monitoring system are. In addition, different machining processes have different demands and limitations for monitoring. This paper considers an analytical approach to define the requirements of a monitoring system. A process failure mode effect analysis (FMEA) is carried out to determine the weaknesses of current production processes. From this analysis, the relationships between failures, causes and effects can be used to populate conditional relationships between process faults and sensor signal features in a monitoring system.

## 1. INTRODUCTION

Most research, testing and industrial application of machining process monitoring systems has considered tool condition monitoring as the primary purpose for monitoring a process [1]. Techniques have been applied to turning, drilling, milling and grinding processes with varying success [2-4]. A number of other research areas have considered a fault detection approach where detection of chatter, depth of cut change or cutting force changes are the objective of the system [5]. Conditional dependencies between different sensor signal features and input variables to a process has been determined by carrying out computations on experimental data, such as neural network methods or correlation analysis [6].

One area lacking in the research is a detailed understanding of the relationship between input variables and the measured effects. This means that where changes are made to

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a process, the change to sensor signals is not clearly understood. Current methods require further experimental data and system training in order to be effective on unproven processes.

The majority of process monitoring applications target solely the detection of process failures, and not the detection of the cause of failure. With functionality to detect cause of failures, a monitoring system is more capable of preventing issues in the manufacturing process since a cause of failure must be known to effectively correct the process. In addition to this, identifying the effects that may occur from a failure is also beneficial, the most commonly used method being on-machine probing for part geometry error measurement.

The first step in understanding the need for a monitoring system for a machining process is to consider what is missing from current processes. For this study, existing machining processes have been interrogated to determine the failures that have occurred, the causes of these failures, the effects from the occurrence and the detection methods currently in use, by conducting an FMEA [7],[8]. An example from the FMEA is given in Table 1.

Table 1. Failure Mode Analysis Worksheet for the Process Step 'Milling Operation'

| Process Step | Potential Failure Mode | Potential Effect(s) of Failure | SEV | Potential Cause(s) of Failure | OCC | Current Process Controls | | DET | RPN |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Prevention of Failure Mode Escape | Detection of Failure Cause | | |
| Run Milling Program | Tool breakage | Geometric part error, tool damage, delay, | 8 | Part condition has changed | 6 | None | Operator observation/CoC | 6 | 288 |
| | | | | Material condition changed | 5 | None | CoC | 8 | 320 |
| | | | | Cutting parameters too aggressive | 6 | None | Double sign off | 5 | 240 |
| | | | | Spindle speed excites part vibration | 5 | None | Tap test / harmoniser | 8 | 320 |
| | | | | Wrong tool used | 4 | Tooling control & spec. | Double sign off | 5 | 160 |
| | | | | Wrong cutting parameters used | 6 | None | Double sign off | 5 | 240 |
| | | | | Tool is worn or damaged | 5 | Tooling control & spec. | Double sign off | 5 | 200 |
| | | | | Part position error changes depth of cut | 4 | None | Double sign off | 7 | 224 |
| | | | | Tool length error changes depth of cut | 4 | None | Double sign off | 7 | 224 |
| | | | | Tool not clamped correctly | 4 | None | Double sign off | 6 | 192 |
| | | | | Excessive cutting force | 5 | None | Operator observation | 6 | 240 |
| | | | | chatter due to tool stiffness | 6 | None | Operator observation | 6 | 288 |
| | | | | chatter due to part stiffness | 5 | None | Operator observation | 6 | 240 |
| | | | | Collision | 4 | None | Operator observation | 6 | 192 |
| | | | | Insufficient coolant flow | 6 | None | Operator observation | 6 | 288 |
| | | | | Incorrect coolant mix | 4 | None | operator observation | 6 | 192 |

By employing this technique, it is clearly shown that the operator is utilised for detection of many failures. In order to build a process where there is little or no reliance on the operator, each one of these failures must now be detected by a monitoring system. The list of potential failures, however, is vast, and so the severity each failure must be considered. The FMEA scoring system covers the severity of the effect, the frequency of occurrence of the cause and the effectiveness of the current process control. As a monitoring system is intended replace the existing process control method, only the severity and occurrence scores are used for ranking the failure mode/cause combinations.

In this example all detection methods that require human intervention are short listed, from this the failures are scored by the severity*occurrence value. The highest scoring failure modes for a generic milling operation are listed in Table 2.

Table 2. Highest scoring failure mode/cause combinations

| Failure Mode | Cause | Score |
|---|---|---|
| Tool breakage | Material property has changed | 48 |
| Tool breakage | Part geometry has changed | 48 |
| Tool pull out | Part geometry has changed | 48 |
| Collision | Part geometry has changed | 48 |
| Tool breakage | Vibration / chatter | 48 |
| Tool pull out | Vibration / chatter | 48 |
| Tool vibration | Tool / tool holder is worn or damaged | 42 |
| Part vibration | Material property has changed | 42 |
| Tool vibration | Material property has changed | 42 |
| Excessive tool wear | Material property has changed | 42 |

For the generic milling process example, all failure modes exhibited the same potential effects as follows:

- Poor surface roughness.
- Re-deposited swarf, chatter marks and other surface effects.
- Localised surface damage or gouges.
- Sub surface damage / poor surface integrity.
- Feature dimension/geometry error.
- Tool holder damage.
- Machine damage.
- Delay to manufacture.

## 2. CAUSE AND EFFECT RELATIONSHIPS

It is vital for a process monitoring system to have consideration of the cause and effect relationships of process faults for intelligent detection and fault diagnosis to be achieved. Experimental data is important to understand these relationships in detail. Using the FMEA described, the failures, causes and effects are listed, however this method does not interrogate the cause and effect relationships. From the FMEA, the key failures can be targeted and an experimental plan can be defined to understand these relationships. The method of interrogating the FMEA data and applying it to a monitoring system is described later in this report.

A common failure shown in the FMEA is premature worn tool condition. A root cause of this failure may be material property change and an effect of this failure may be poor surface finish. Several other interactions occur during this process that result from the root-cause and these have been termed meta-causes, for example increased cutting force. This example is illustrated in Fig. 1.

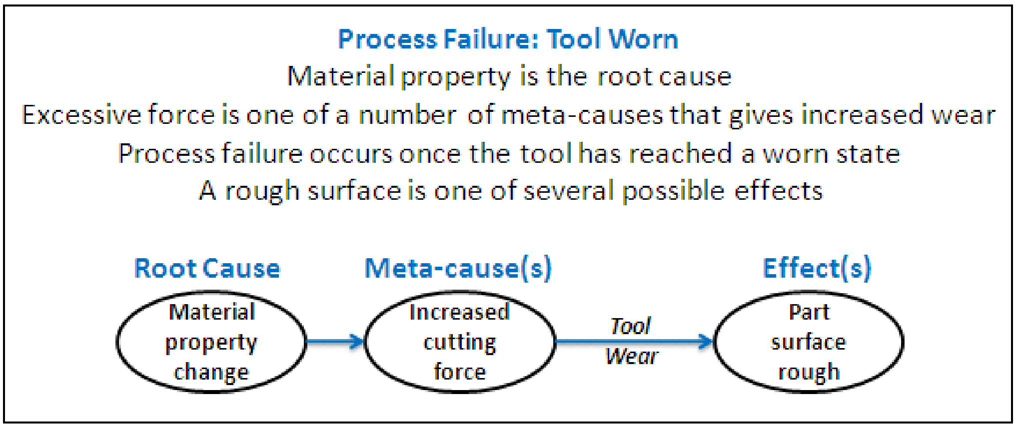


Fig. 1. Example of a cause and effect relationship

With understanding of the cutting process, a number of meta-causes can be proposed for each failure mode. Experimental data can then be used to determine the detect-ability of these interactions. The above example can be expanded to that shown in Fig. 2.

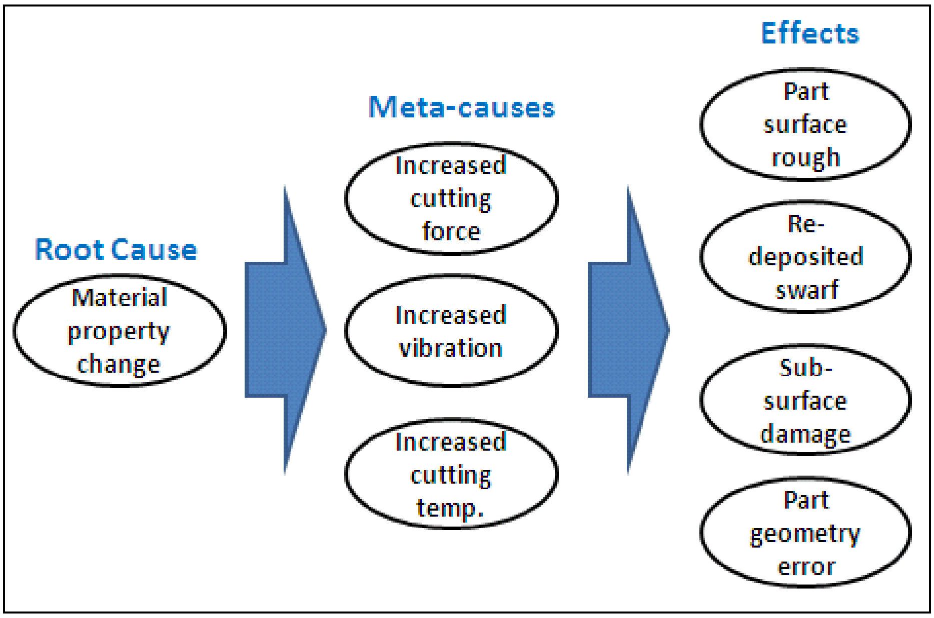


Fig. 2. Multiple meta-causes and effects from a single root cause

## 3. IN PROCESS MEASUREMENT OF META CAUSES AND EFFECTS

The meta-causes can also be perceived as effects of the root cause and generally speaking they occur during the machining process. For measurement of their occurrence, real time indirect measurement is most achievable in a production process. For example, vibration, acoustic emission (AE) [9] and spindle power measurement.

In this application, the effects from each failure mode are in fact work piece or process defects and so for the following descriptions they will now be referred to as defects. Where measurement capability exists, the defects can be measured intermittently by direct measurement with inspection probes, roughness tester's etc. Measurement of both meta-causes and defects should be considered for the most comprehensive monitoring system.

Finally, from the FMEA data, the interactions between all meta-causes, root causes and defects should be defined. For these relationships to be modelled, a network of interactions is required rather than the flow diagram example in Fig. 2., Fig. 3. shows the form that these relationships take in a directed acyclic graph (DAG).

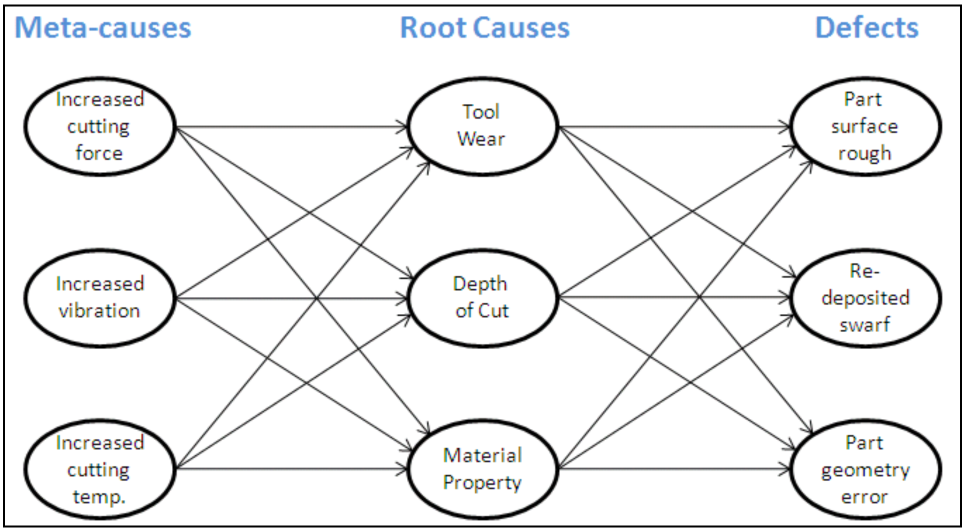


Fig. 3. Example DAG associating meta-causes, root causes and defects

A monitoring system would use the relationships defined in Fig. 3. in two ways:

(i) The meta-causes would be measured and a root cause would be diagnosed. The defect(s) would then be anticipated and either measured in process (where a method to do so exists) or the user would be informed of the potential defect.

(ii) The system would be retrospectively informed of the defect, either from measurement equipment or an operator input. The system would then infer the most likely root cause of this error from the previous meta-cause measurement data.

One advantage from using the above functions is that the system can be self learning and improve its diagnosis performance based on previous results.

## 4. EXPERIMENT AND RESULTS

Using the techniques described, a process monitoring system has been defined and tested. The process of designing the system is shown in this section, followed by the results given from machining trials.

First, an FMEA has been conducted choosing a profile milling operation on Titanium 6-4 as the process step in question. The FMEA scoring was completed by a number of manufacturing engineers with a wide experience in aerospace manufacturing. 19 different failure modes were identified for the milling process and for these, a total of 23 causes were recorded.

For this example, the three most frequent and highest scoring causes are targeted by the monitoring system and these were found to be:

- Material geometry variation.
- Material properties, such as hardness.
- Tool condition or tool life.

All of which are key process inputs to all machining processes. Furthermore, these had little or no detection methods other than the reliance on skilled operators. These causes were responsible for a number of failure modes as follows:

- Part vibration.
- Tool vibration.
- Fixture failure.
- Collision.
- Tool pull-out.
- Tool breakage.
- Tool wear.

The meta-causes or measurable effects associated with each of the causes and failures were identified as follows:

- Vibration.
- Cutting force.
- AE.
- Temperature.
- Spindle power.

The measureable effects from occurrence of the process failures were identified as:

- Part geometry.
- Tool geometry.
- Part surface roughness.

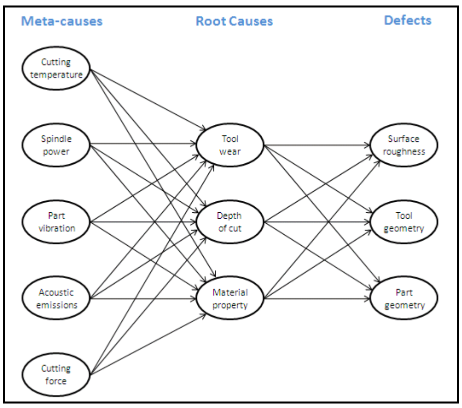


Fig. 4. Cause, meta-cause and effect DAG for profile milling of Titanium

This data can now be used to define the associations between causes, meta-causes and effects from the process failures. The network diagram in Fig. 4. illustrates this. Similar strategies, such as Bayesian networks, have proven to be an effective way of analysing a network of relationships between elements of a machining system [10],[11].

For the experimental demonstration of this methodology, the DAG shown in Fig. 5. has been simplified to that shown in Fig. 5.

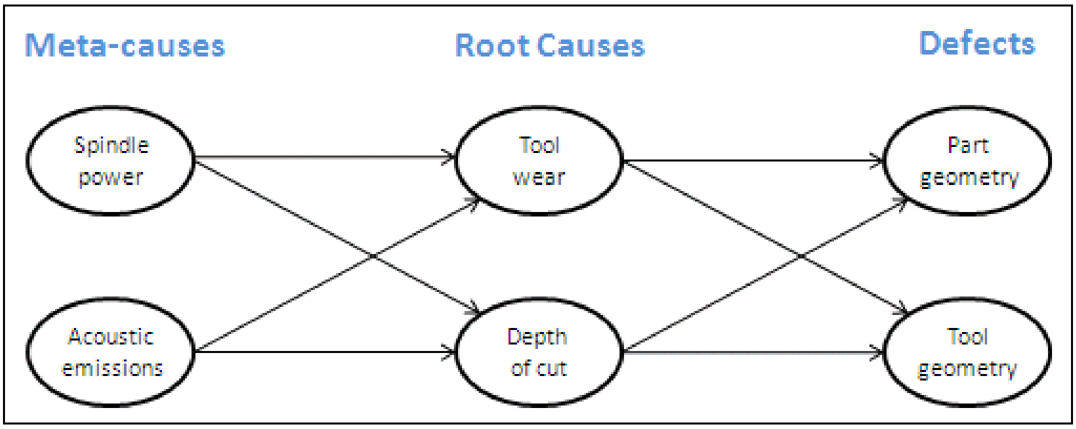


Fig. 5. Cause, meta-cause and effect DAG for experiment

An experiment has been conducted in order to determine the conditional dependencies between each node in Fig. 5. In addition to this, scaling factors have been determined for the sensor signals of spindle power and AE.

Using a 16mm diameter, 4 flute solid carbide end mill, profile milling operations were conducted on a 730mm long titanium 6-4 test piece. Spindle power and AE RMS measurements were taken for each cut. Tool wear measurements were taken routinely during the trials until tools reached a flank wear of 0.2mm, at which point the tool is deemed completely worn. Radial depth of cut was incremented from 0.5mm to 3mm in 0.5mm steps. Axial depth of cut was kept constant at 10mm. The experimental set up is shown in Fig. 6.

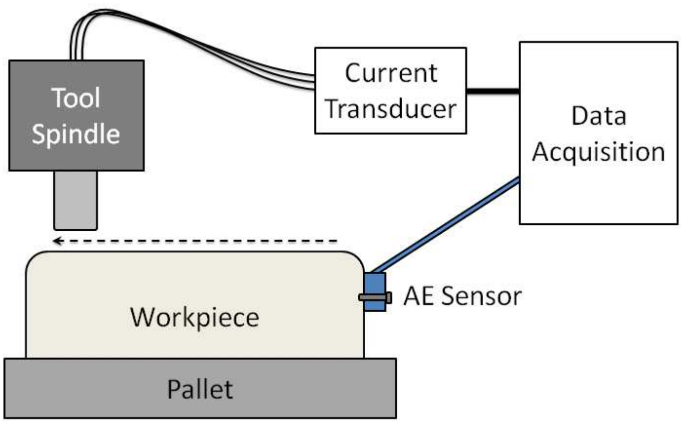


Fig. 6. Experimental set up for profile milling trials

In addition to categorising the tool wear state by the level of flank wear; this is also done by calculating the % of tool life consumed as a function of metal removed. Using this method can be more practical in production processes as it provides quick and automated method of teaching a system such as this, without the need for time consuming tool measurements. Table 3 shows the tests completed and corresponding results for tool wear, AE RMS and spindle power.

Table 3. Tests conducted to determine sensor signals relationship to depth of cut and tool wear

| Test # | Tool Flank Wear (mm) | Metal Removed (cm3) | Tool life consumed (%) | Depth of Cut (mm) | AE RMS Magnitude | Spindle Power |
|---|---|---|---|---|---|---|
| 1 | 0.04 | 3.7 | 0.7 | 0.5 | 0.075 | 1.023 |
| 2 | | 11.0 | 2.0 | 1.0 | 0.093 | 1.666 |
| 3 | | 21.9 | 4.1 | 1.5 | 0.108 | 2.233 |
| 4 | | 36.5 | 6.8 | 2.0 | 0.121 | 2.734 |
| 5 | | 54.8 | 10.2 | 2.5 | 0.132 | 3.276 |
| 6 | | 76.7 | 14.3 | 3.0 | 0.131 | 3.761 |
| 7 | 0.05 | 80.3 | 15.0 | 0.5 | 0.076 | 1.062 |
| 8 | | 87.6 | 16.3 | 1.0 | 0.087 | 1.604 |
| 9 | | 98.6 | 18.4 | 1.5 | 0.097 | 2.187 |
| 10 | | 113.2 | 21.1 | 2.0 | 0.105 | 2.760 |
| 11 | | 131.4 | 24.5 | 2.5 | 0.113 | 3.280 |
| 12 | | 153.3 | 28.6 | 3.0 | 0.117 | 3.852 |
| 13 | 0.07 | 157.0 | 29.3 | 0.5 | 0.068 | 1.057 |
| 14 | | 164.3 | 30.6 | 1.0 | 0.080 | 1.739 |
| 15 | | 175.2 | 32.7 | 1.5 | 0.090 | 2.312 |
| 16 | | 189.8 | 35.4 | 2.0 | 0.100 | 2.859 |
| 17 | | 208.1 | 38.8 | 2.5 | 0.107 | 3.391 |
| 18 | | 230.0 | 42.9 | 3.0 | 0.112 | 3.909 |
| 19 | 0.10 | 233.6 | 43.5 | 0.5 | 0.065 | 1.134 |
| 20 | | 240.9 | 44.9 | 1.0 | 0.076 | 1.790 |
| 21 | | 251.9 | 46.9 | 1.5 | 0.087 | 2.363 |
| 22 | | 266.5 | 49.7 | 2.0 | 0.095 | 2.922 |
| 23 | | 284.7 | 53.1 | 2.5 | 0.103 | 3.504 |
| 24 | | 306.6 | 57.1 | 3.0 | 0.111 | 4.027 |
| 25 | 0.12 | 310.3 | 57.8 | 0.5 | 0.066 | 1.216 |
| 26 | | 317.6 | 59.2 | 1.0 | 0.076 | 1.774 |
| 27 | | 328.5 | 61.2 | 1.5 | 0.085 | 2.392 |
| 28 | | 343.1 | 63.9 | 2.0 | 0.095 | 3.032 |
| 29 | | 361.4 | 67.3 | 2.5 | 0.101 | 3.587 |
| 30 | | 383.3 | 71.4 | 3.0 | 0.104 | 4.185 |
| 31 | 0.18 | 386.9 | 72.1 | 0.5 | 0.064 | 1.318 |
| 32 | | 394.2 | 73.5 | 1.0 | 0.075 | 1.922 |
| 33 | | 405.2 | 75.5 | 1.5 | 0.083 | 2.574 |
| 34 | | 419.8 | 78.2 | 2.0 | 0.089 | 3.175 |
| 35 | | 438.0 | 81.6 | 2.5 | 0.092 | 3.793 |
| 36 | | 459.9 | 85.7 | 3.0 | 0.096 | 4.389 |
| 37 | 0.21 | 463.6 | 86.4 | 0.5 | 0.060 | 1.441 |
| 38 | | 470.9 | 87.8 | 1.0 | 0.068 | 2.009 |
| 39 | | 481.8 | 89.8 | 1.5 | 0.075 | 2.699 |
| 40 | | 496.4 | 92.5 | 2.0 | 0.081 | 3.366 |
| 41 | | 514.7 | 95.9 | 2.5 | 0.086 | 4.059 |
| 42 | | 536.6 | 100.0 | 3.0 | 0.089 | 4.852 |

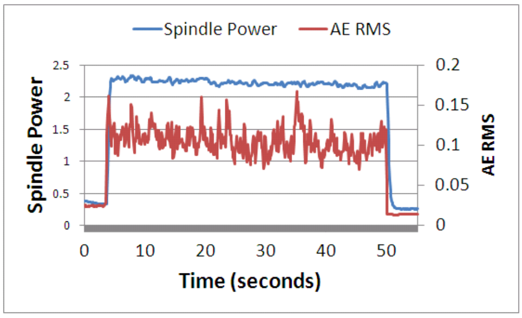


Fig. 7. Sensor signal time graph for 1.5mm radial depth of cut and a new tool. Entry to cut can be seen at approximately 4 seconds on the x axis, and exit from cut can be seen at approximately 50 seconds

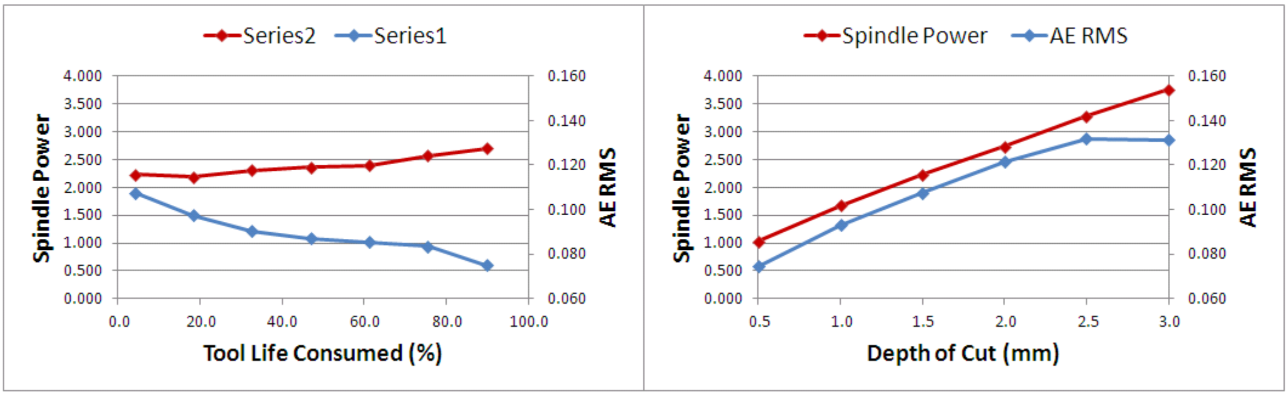


Fig. 8. Observed relationships between depth of cut and tool life from experimental data. Note; tool life consumed is a measure of metal removed by tool

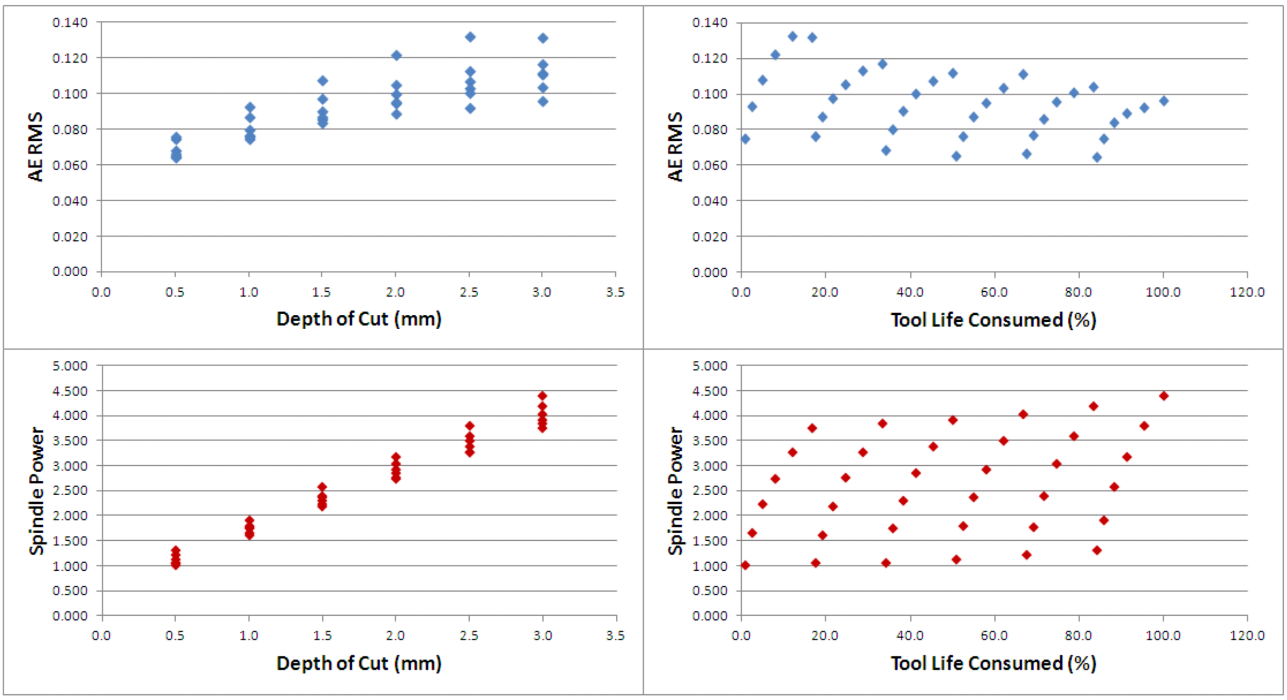


Fig. 9. All test results for spindle power and AE RMS. Note; tool life consumed is a measure of metal removed by tool

Fig. 9. shows all the results from the experiment.

Fig. 8 shows two graphs; the first shows the change in AE RMS and spindle power as the tool wears, only observing tests using a depth of cut of 1.5mm. The second graph shows the change in AE RMS and spindle power as the depth of cut changes, using a new tool. It can be seen that depth of cut has a larger influence on the magnitude of both AE RMS and spindle power than tool wear. It can also be observed that AE RMS reduces as the tool wears.

The results shown have been analysed using design of experiment software, MODDE from Umetrics. Using partial least square (PLS) fitting the coefficients that relate the factors to the responses can be determined. A linear relationship has been assumed for this model. From the experimental data shown above, the coefficients define the equations shown in Fig. 10.

**AE RMS = X1 * Tool Condition + Y1 * Depth of Cut + Z1**
**Spindle Power = X2 * Tool Condition + Y2 * Depth of Cut +Z2**

X1 = 0.07608, Y1= -0.00035, Z1 = 0.01839, X2 = 0.32251 Y2 = 0.00705, Z2 = 1.14427.

Fig. 10. New descriptor using AE RMS and spindle power data. These simultaneous equations can be rearranged to give a calculation for tool condition and depth of cut from sensor data

The data has produced a model of a good fit as can be seen in Fig. 11. - the output from the PLS analysis.

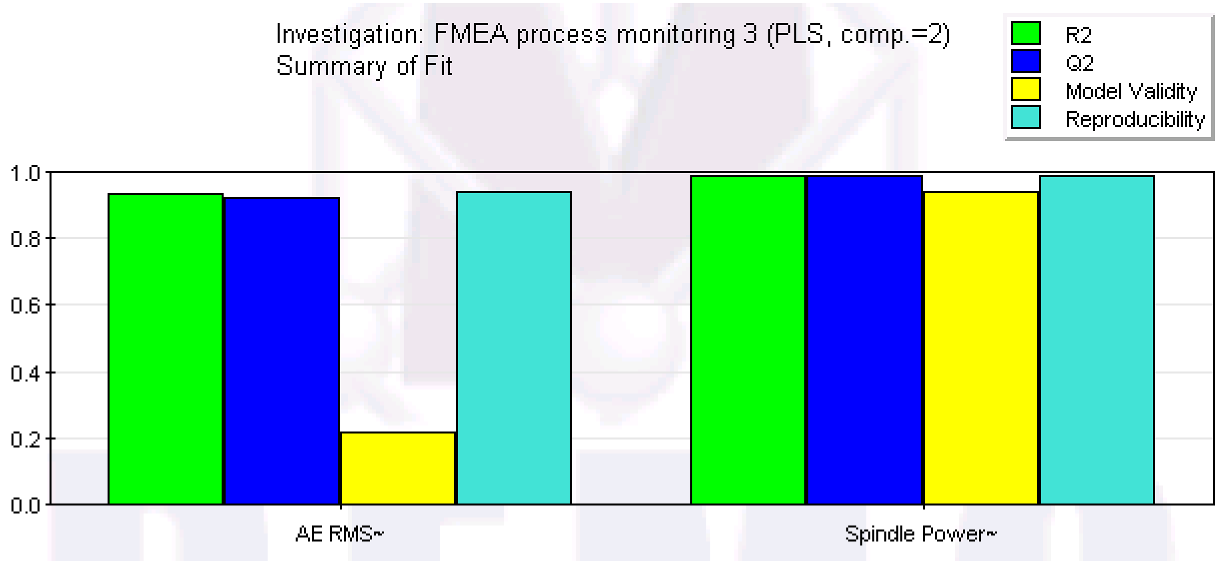


Fig. 11. Summary of fit of data in PLS model. Note that R2 is the coefficient of multiple determination, where a value near to 1 indicates a good fit of the data in the model. Q2 is the fraction of the variation of the response predicted by the model, where a value near 1 indicates good predictability of the model

The coefficients obtained from the model can be used to populate the DAG diagram shown previously in Fig. 4.2, defining the relationships between each node. Fig.12. shows the predicted depth of cut and tool condition obtained from the model equations. It also shows a good fit to the actual values of depth of cut and tool condition.

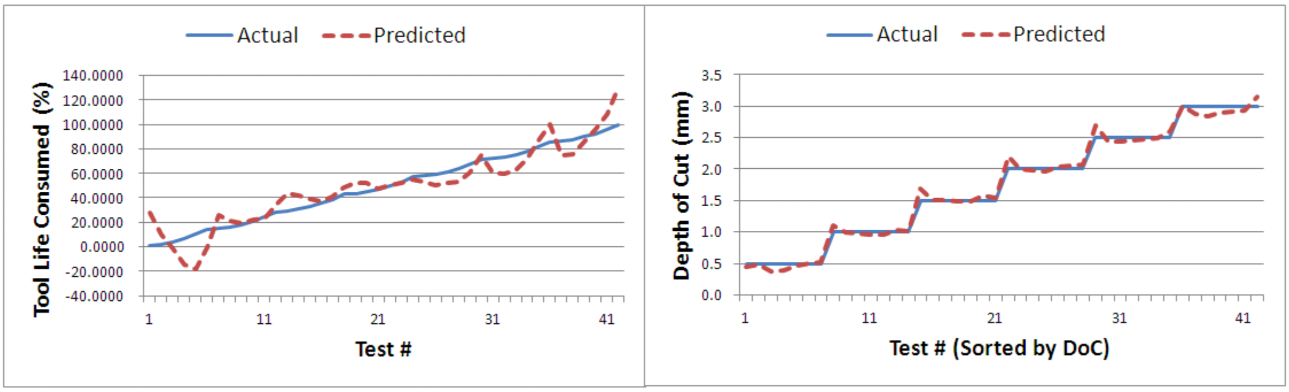


Fig. 12. Actual vs. Predicted tool condition and depth of cut. Note; tool condition is a measure of metal removed by tool

## 5. CONCLUSIONS

A methodology for building a process monitoring system to enable fault detection in a milling process has been described. A system capable of determining root cause of process variation has been demonstrated on a common production problem where both depth of cut and tool condition can vary and impact on the performance of the machining process.

It has been shown that depth of cut increases spindle power and acoustic emission measured during machining. Tool condition has been shown to affect the signals to a lesser extent where RMS magnitude increases with depth of cut increases and decreases with tool wear.

Using both spindle power and acoustic emission signal magnitude, the model obtained from experimental data has been shown to clearly differentiate between depth of cut change or tool condition change using these sensor signals alone. Depth of cut has been shown to be fit to the actual values accurately, within 0.1mm using this system. Tool life has been assessed by the amount of work done by the tool (metal removed) and gives a fit to within 10-20% of the tools life.

Using the methodology defined, fault detection systems can be designed and built with minimal expense. Customised systems can therefore be implemented and tested on many production scenarios, providing a more flexible tool for process monitoring than is used in current aerospace manufacturing processes.

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