ENS 492 – Graduation Project (Implementation) Final Report

Sabancı Üniversitesi

Project Title

Monitoring of Grinding Operations

Group Members

Mustafa Göktürk Yandım

Özüm Başkan

İlayda Tukuş

Çağatay Yağız Uysal

Supervisor

Erhan Budak

Assistant

Hamid Jamshidi

Date

30.05.2021

Contents

Table of figures

1. EXECUTIVE SUMMARY

The present modern manufacturing industry demands more on remotely working autonomous machines that can achieve better results in terms of quality and time efficiency. However, this new demand brings its own variety of challenges for different manufacturing processes. In that case, grinding is one of these fundamental manufacturing processes which is usually the last step in a manufacturing process that is crucial for a good surface and finishing quality. Grinding processes are carried out on precision machine tools using abrasive tools which are composed of thousands of hard particles or grains for removing small amounts of material from the parts surface. Being usually the last process on a part, performance of these processes is of utmost importance to ensure the surface integrity.

The proper operating conditions can be ensured by using a process monitoring system based on sensory information. A special type of sensor called Acoustic emission sensor becomes handy since it is easier to implement and gives more advantages over other sensors. AE sensor is a passive method that can detect sudden or rapid energy releases or changes from the sources in the current working medium. These energy releases may come from objects that are under high changing stresses. AE sensor samples those energy changes in different frequencies and outputs a continuous waveform signal in time and magnitude space.

In this project context, we are aiming to design and implement an intelligent monitoring system for grinding processes. The monitoring system will receive real time data from machine implemented AE sensors. Then this data will be processed with necessary tools to remove disturbing factors like noises and non-working zones. After that, features will be extracted from the gathered processed signal data, or a different program will be used to compare these data with previously introduced correct data. These two ways have their own advantages to get necessary information about the ongoing process. The feature extraction method provides some features from the signal like minimum value, maximum value, skewness, kurtosis etc. where these features will be used to get necessary information about the process. On the other hand, this comparison method works with different techniques. In the grinding process there are some input parameters which are given by the operator in the first place, this method takes these parameters and finds correct test data from the database. Then creates new data which is based on the differences of the given test and correct data from the database. As a result of these features or/and this comparison data will be used to train a Machine Learning Model. This model will be used as a guide to predict whether an ongoing grinding process is normal or abnormal (failed).

2. PROBLEM STATEMENT

In this project context, we are aiming to design and implement an intelligent monitoring system for grinding processes. The monitoring system will analyze the data from machine implemented AE sensors. After that, the gathered AE signal will be analyzed in the frequency domain to be compared with an ideal process which is already stored in a Database. Using a coherence estimation between the ideal data and the new grinding process we will try to estimate whether the current grinding operation is normal or abnormal (failed).

The project aims to solve a complex problem that have variety of challenges and constraints such as:

● The problem involves infrequently encountered grinding process related issues that need to be simulated for data collection.

● The problem involves physical constraints due to the nature of the grinding operation environment.

● Research and simulation-based experience/information is required for more analytical solution methodology.

2.1. Objectives/Tasks

- **Acoustic Emission Sensor usage/ signal reading, we** got familiarized with Acoustic Emission Sensors to get proper/useful signal outputs and implementing AE sensor to grinding operations to monitor process signals.
- **Machine learning algorithm development,** we developed a program which can detect the difference between the correct data and the data of a given test, and as a result, we were able to predict or detect the errors.

- **Doing more research on smoothening methods and selecting an appropriate one**. After all, we decided to use the Savitzky-Golay smoothing method which smooths according to a quadratic polynomial that is fitted over each window of A. This method can be more effective than other methods when the data varies rapidly.
- **Extracting more features and deciding on which of these are more relevant and useful.** Instead of getting more features, we develop different algorithms to compare data. This algorithm helped us to understand what happens when different parameters change in our tests and how they affect our signals.
- **Software & real-life Simulations,** because of the current pandemic situation to gather useful data of the variety of conditions or failures that occur during grinding operations, we couldn't work with machines. As a result, we did research and used the given tests to create this data.
- **Research on possible grinding process related failures and issues**. We did necessary literature research.
- **Creating or finding (if possible) some failed process data to be included in the model.** After the observation of parameter changes and literature research, we create signals with errors.

2.2 Realistic Constraints

Process Environment: Grinding operations are mostly conducted in harsh environmental conditions where a high RPM grinding disc continuously rubs a workpiece forming small metal swarf particles with sparks or lubricant splashes when used.

Sensor Implementation: Acoustic emission sensor that we use for monitoring grinding progress is a passive sensor that detects rapid or sudden energy releases and outputs waveforms. In that case, there are a variety of parameters that may affect the quality of output data such as sensor placement, sampling rate, propagation medium etc. In that case, some adjustments may be necessary for better analysis of the process. Due to the pandemic, we were not able to be in the lab environment, our teaching assistant took care of the sensor implementation.

Data Collection: To create a more generally applicable and accurate grinding monitoring system, a variety of data from different grinding operations are required where different grinding discs, shapes, RPM rates, workpiece materials, lubricants etc. are used. Due to the pandemic, we were only able to collect a few data from one specific grinding operation.

Economic: Our monitoring algorithms or solutions should be precise where it can identify the causes of process related failures correctly. Otherwise, unnecessary solutions or suggestions of our monitoring system might lead to redundant part changes or actions that might have economical damage. (i.e., discarding the grinding disc even if it is still usable or in good condition). Throughout the process, we did not come across any economic damage.

Health and Safety: Our monitoring system is planned to be an autonomous system where no or little human interaction is needed. However, our methodologies or implementations should be safe for human workers and avoid any dangers that may be harmful. As far as we proceed, we did not encounter any health or safety issues.

Adaptability: To design a monitoring system that can be implemented in various cases or scenarios; We need to consider different parameters such as type of grinding operation, type of used disc material & characteristics, type & characteristics of used lubricant, grinded material type, used grinding machine etc. In fact, our self-learning algorithms should have been able to adopt and act according to these parameters. Due to the pandemic, we were only able to adapt the parameters of one specific grinding operation.

3. METHODOLOGY

We created a program that can monitor and analyze the grinding processes by looking at the output of the Acoustic Emission sensor Data. We first explained our Algorithm steps in 5 sections below (3.1 to 3.5) and then described the overall program algorithm at the last section F. Appendix 2 also shows the complete methodology as a visual diagram.

3.1 Experiment Data

In our project context, we needed a variety of Acoustic Emission sensor data from different grinding process conditions. Since we were not able to conduct these due to the recent COVID-19 pandemic, our project Assistant Hamid Jamshidi shared his previous experiment dataset that includes Acoustic Emission sensor measurements of different grinding processes with different parameters or settings. We used these datasets throughout our project.

3.2 Cropping & Smoothening

Original data is not suitable to work with because we have starting and ending periods of our grinding process. In these periods, we have nothing but noise so first we crop these periods as shown in Figures 1. We developed FindPlotStart and FindPlotEnd functions which find the start and finish points of our process respectively.

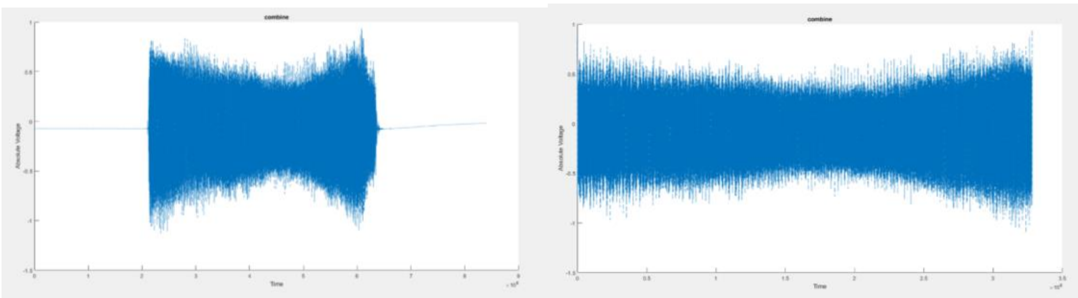


Figure 1 Uncropped and cropped raw signal

Second part is to smooth data to remove noise from necessary data. There are so many ways to smooth data, after our research we decided on the Savitzky-Golay smoothing method which smooths according to a quadratic polynomial that is fitted over each window of A. This method can be more effective than other methods when the data varies rapidly. As shown in Figure 2 while noise is being filtered, data is conserved properly.

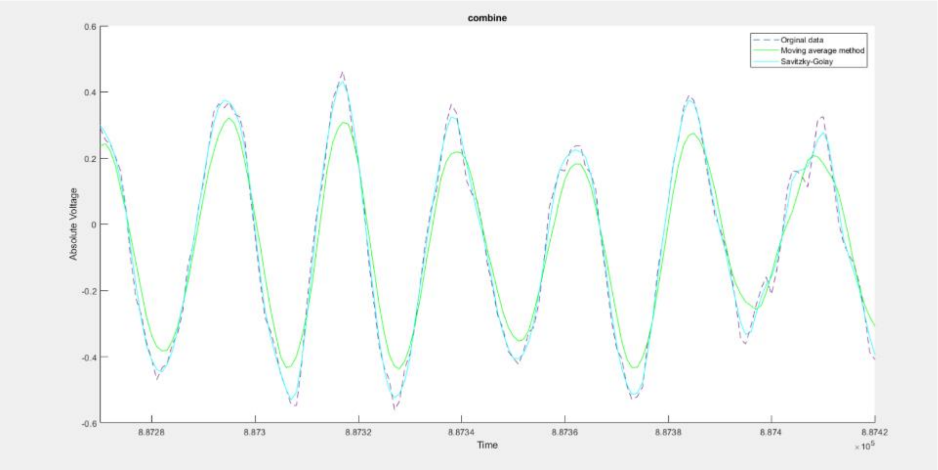


Figure 2 Signal smoothing methods

How about the window width? Well, we need to set a width that is small compared to the main features of our spectrum, and large compared to the noise. Setting the width in this range does a much better job in smoothing out the noise. In figure 3, different window widths 1.5, 5 and 10 can be seen. In our case the reduction is mild, however increasing the width even further must be done with caution, as we'd start to wash away the important features of the spectrum (see red line).

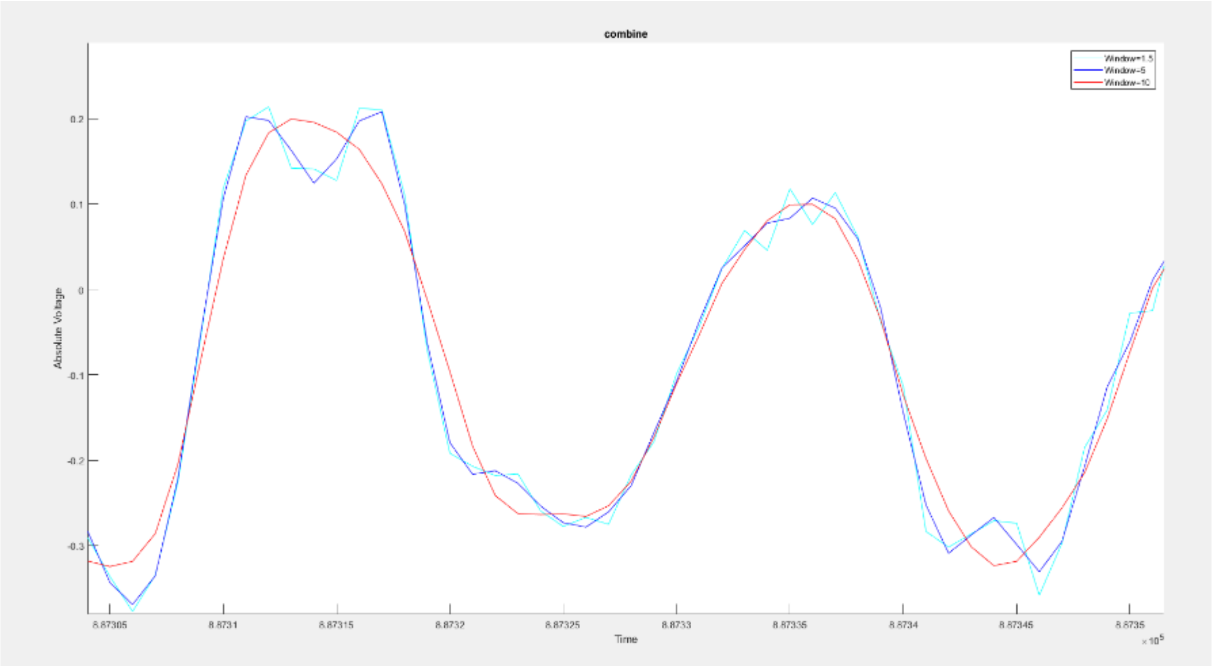


Figure 3 Spectral Analysis

3.3 Spectral Analysis

Time series data shows periodical behavior which can be complex for analysis. In that case Spectral analysis is a helpful methodology that helps us to examine the underlying details in the signal (Jones,2018).

Fourier Transform (Lei, 2011)

We assume a discrete time-series with a finite number of samples N and a sampling time interval T_s between two successive samples

$$x_n = \{x_0, x_1, \ldots, x_{N-1}\} \quad (1)$$

According to the mathematical theory of Fourier analysis, the above time-series can be represented by the following inverse finite Fourier transform:

$$x_n - \bar{x} = \frac{1}{N}\sum_{m=1}^{N-1} G(m)\, e^{j2\pi mn/N} \quad (n = 0, 1, \ldots, N-1) \qquad (2)$$

where $\bar{x}$ is the average value of the time-series, j = $\sqrt{-1}$ denotes the symbol of complex number and $e^{j\theta}$ is a complex sinusoidal function (Note: $e^{j\theta} = \cos\theta + j\sin\theta$). G(m) is the spectral density function (or weighting function) mentioned previously which can be calculated from the following finite Fourier transform

$$G(m) = \sum_{n=0}^{N-1}(x_n - \bar{x})\, e^{-j2\pi(m/NT_s)nT_s} = \sum_{n=0}^{N-1}(x_n - \bar{x})\, e^{-j2\pi mn/N}$$

$$(m = 0, 1, \ldots, N-1) \qquad (3)$$

where $m/NT_s = f_m$ is the discrete frequency and $nT_s = t_n$ is the discrete time. It should be noted that the $(x_n – x)$ in Equation (1) and the G(m) in Equation (2) are equivalent measures in time and frequency domains, respectively, which are related to each other by the Fourier transform. T_s does not appear in Equations (2) or (3) and is only used as a scaling factor when calculating frequencies.

After cropping the data and applying a smoothing operation on the interest area in the data, we continued our analysis with spectral analysis. In that case we used MATLAB's pspectrum() function to convert the data in the frequency-power domain. This function finds a compromise between the spectral resolution achievable with the entire length of the signal and the performance limitations that result from computing large FFTs; it computes a Welch periodogram to divide the signal into overlapping segments, windows each segment using a Kaiser window, and averages the periodograms of the segments. At the end it outputs the power-frequency plot of the input data as figure 4 shows below (Mathworks, 2021). This enabled us to compare different tests and analyze the frequency differences between them (Figure 5).

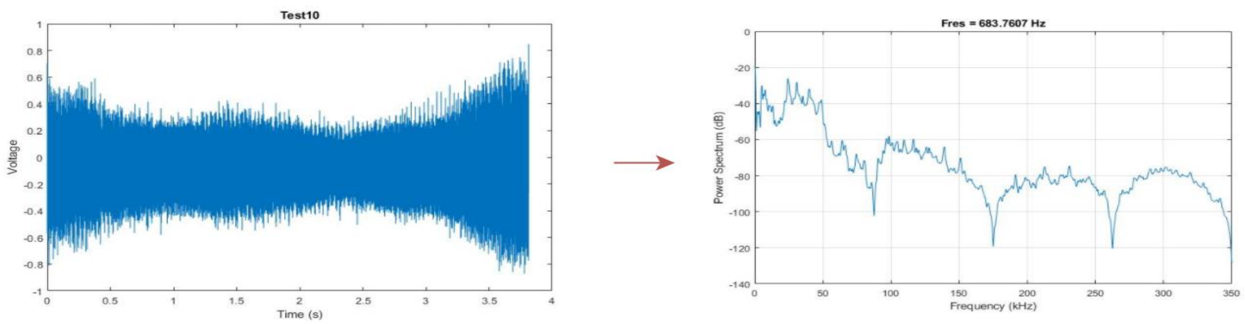


Figure 4 Time to Frequency Domain conversion of Test 10

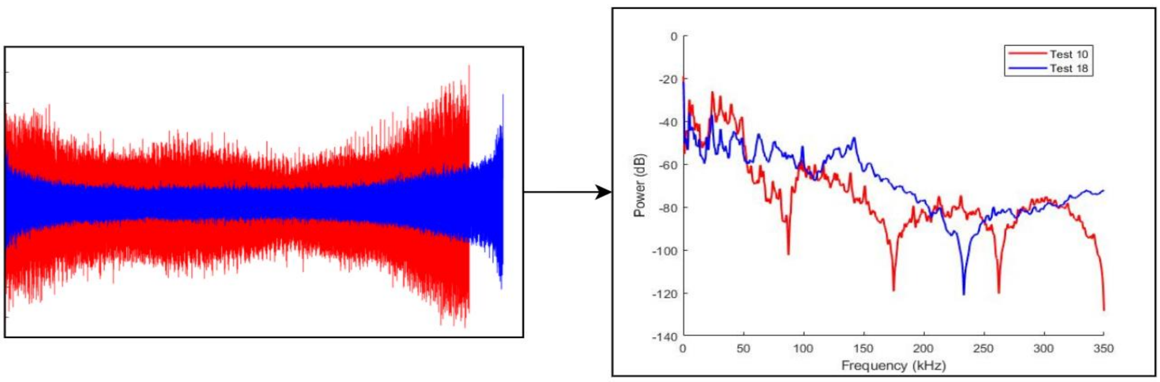


Figure 5 Comparison between Test 10 (Coolant OFF) & Test 18 (Coolant On)

3.4 Correct Measurement Database

In our solution methodology, since we do not have access to more data or conditions to do more experiments, we used the experiment data that our project assistant Hamid Jamshidi provided. In that case, we created a struct to create a database that holds these correct measurements in a sorted manner as Appendix 1 shows. We did not include some of the original tests that were not relevant or useful. For example, 1st and 2nd experiments were conducted to record the environment noise and the working wheel noise where there is no actual grinding operation thus no actual contact between the wheel and the material. Also, some experiments were just repeating of the same ones thus we also neglected them in our database. Here below figure 6 shows the tests that we included (green ones) in the database.

Test number	Feed rate(mm/min)	Depth of cut(micron)	Wheel speed(RPM)	Sensor Position	sampling rate(Hz)	Coolant Fluid
1					700000	off
2					700000	off
3	1200	0	1500	workpiece	700000	off
4	1200	2	1500	workpiece	200000	off
5	1200	2	1500	workpiece	400000	off
6	1200	2	1500	workpiece	700000	off
7	1200	2	1500	workpiece	700000	off
8	800	2	1500	workpiece	700000	off
9	1800	2	1500	workpiece	700000	off
10	1200	4	1500	workpiece	700000	off
11	1200	8	1500	workpiece	700000	off
12	1200	2	1000	workpiece	700000	off
13	1200	2	2000	workpiece	700000	off
14	1200	2	2000	workpiece	700000	off
15	1200	2	1250	workpiece	700000	off
16	1200	0	1500	workpiece	700000	ON
17	1200	2	1500	workpiece	700000	ON
18	1200	4	1500	workpiece	700000	ON
19	1200	8	1500	workpiece	700000	ON
20	1200	2	1000	workpiece	700000	ON
21	1200	2	2000	workpiece	700000	ON
22	1200	8	1500	workpiece	200000	ON
23	1200	8	1500	workpiece	200000	ON
24	1200	2	1500	table	700000	OFF

Figure 6 Tests we selected from the original tests list (labeled in green)

In fact, it is possible to simply expand this database (Appendix 1) in future with the new experiments that were done with various parameters such as feed rate, depth of cut etc.

Using the database

Since we created this database in a struct format, we can easily find the corresponding original data using a dot notation with the parameters.

Here is a demonstration: Let's assume we want to conduct a new test with these parameters:

Feed rate of 1200 mm/min, Depth of cut of 4 microns, Wheel RPM of 1500 with 70000 sampling rate and using a coolant.

We just simply combine these parameters in the order below:

```
% Find the corresponding Data from the Dataset
fromDatabase = DATA.("f" + feedRate).("d" + depthOfCut).("RPM" + RPM).("freq" + freq).(coolant);
```

In our case this becomes:

fromDatabase = DATA.f1200.d4.RPM1500.freq7.ON;

Now we found and stored the corresponding experiment data in the "fromDatabase" variable. We can check the name of the test using:

```
>> fromDatabase.Props.name

ans =

    'test18.tdms'
```

Thus, with the given parameters, we found that there exists data with the same parameters in the database with the name of the test18 as it can be verified from the figure 5 too.

3.5 Coherence Estimation

The magnitude-squared coherence estimate is a function of frequency with values between 0 and 1. These values indicate how well x corresponds to y at each frequency. This method is used to compare the processed version of the given test data and the correct test data from the database which is created with the given correct test result. As a result, this method helps us to observe coherence estimation between two data in each frequency domain.

The coherence between two signals x(t) and y(t) can be defined in this formulation:

$$C_{xy}(f) = \frac{|G_{xy}(f)|^2}{G_{xx}(f)G_{yy}(f)}$$

where $G_{xy}(f)$ is the Cross-spectral density between x and y, and $G_{xx}(f)$ and $G_{yy}(f)$ the auto spectral density of x and y respectively. The magnitude of the spectral density is denoted as |G|. The coherence function estimates the extent to which y(t) may be predicted from x(t) by an optimum linear least squares function.

Values of coherence will always satisfy $0 \leq C_{xy}(f) \leq 1$ For an ideal constant parameter linear system with a single input x(t) and single output y(t), the coherence will be equal to one. To see this, consider a linear system with an impulse response h(t) defined as: $y(t) = h(t) * x(t)$where * denotes convolution. In the Fourier domain this equation becomes $Y(f) = H(f)X(f)$

where Y(f) is the Fourier transform of y(t) and H(f) is the linear system transfer function. Since, for an ideal linear system: $G_{yy} = |H(f)|^2 G_{xx}(f)$ and $G_{xy} = H(f)G_{xx}(f)$ and since $G_{xx}(f)$is real, the following identity holds,

$$C_{xy}(f) = \frac{|H(f)G_{xx}(f)|^2}{G_{xx}(f)G_{yy}(f)} = \frac{|H(f)G_{xx}(f)|^2}{G_{xx}^2(f)|H(f)|^2} = \frac{|G_{xx}(f)|^2}{G_{xx}^2(f)} = 1$$

In addition, we also used coherence estimation to observe differences between data signals of tests which have one parameter difference between them. With this methodology, we could understand the effects of parameters on different frequencies.

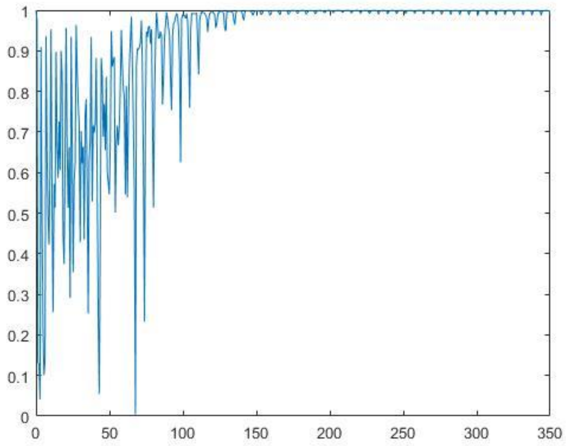


Figure 7 Coherence feed rate change

In figure 7, we used tests 6 and 9 where every parameter is identical except the feed rates.

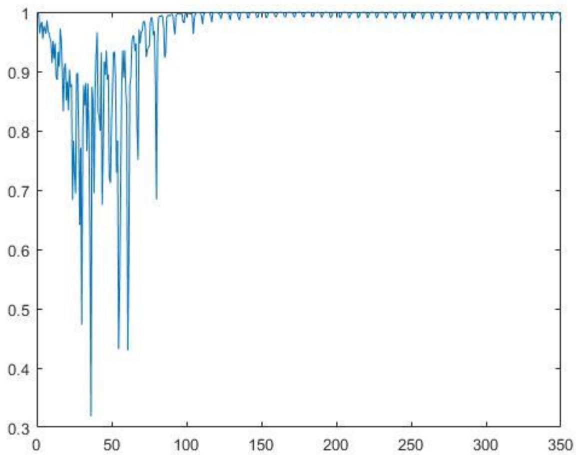


Figure 8 Coherence depth of cut change

In figure 8, we used tests 17 and 19 where every parameter is identical except the depth of cut.

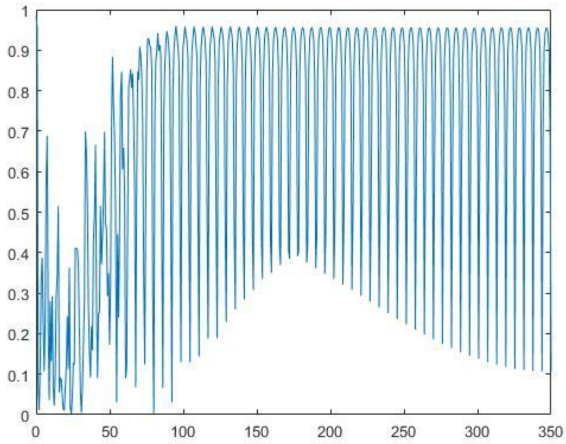


Figure 9 Coherence coolants change

In figure 9**,** we used tests 10 and 18 where every parameter is identical except the coolant on/off situations.

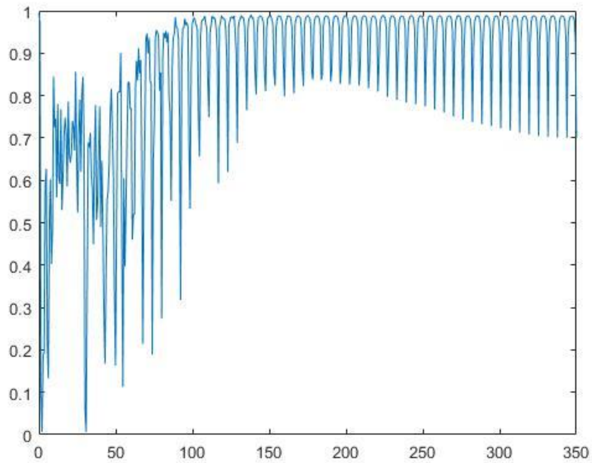


Figure 10 Coherence wheel speed change

In figure 10, we used tests 12 and 13 where every parameter is identical except the wheel speeds.

As a result of this methodology, we observed that every parameter change effects can be seen on different frequencies. In future phases, if we don't have exact parameters given, with these results we can estimate these parameters.

3.6 Algorithm

We developed a coherence algorithm in Matlab where we combined the functions and the methodologies that are explained in upper sections (A-E). Please refer to the Appendix 2 Part 1 & 2 for the visualization of the algorithm which is also described in words below.

How Does It Work?

1. An operator or user sets the parameters for the new grinding operation including:
    a. Feed Rate
    b. Depth of Cut
    c. Wheel RPM
    d. Sampling Rate
    e. Coolant ON/OFF
2. Our program takes these parameters and searches the database for an experiment that was conducted with the same parameters and returns it's Acoustic Emission sensor output data (we called this as original experiment data).
3. Original experiment data is now divided into 5 equal length sections corresponding to the 20 % of the whole data.
4. Acoustic Emission sensor starts to measure the new experiment and it is also divided into sections as the data comes.
5. Once the AE sensor gathers the complete data of a sector from the new experiment, we apply a smoothing operation to both original data sector and the new experiment sector.
6. Outputs of these smoothened experiments are then converted to the Frequency-Power domain using the Fourier transform.
7. Frequency-Power outputs (Spatial analysis) of both original and new experiment sectors are then compared using a coherence function. This outputs a coherence-frequency graph that shows the coherence estimations (0-1 range) of the certain frequencies between two datasets.
8. Since we have a wide frequency range in the coherence spectrum (0-350 khz), we again divided this data into equal sectors with increments of 7Khz intervals.

[0-7 kHz] , [7-17 kHz] …….. [343- 350 khz]

9. For each 7 kHz frequency interval of the current sector's coherence estimate, we calculated the mean values. For 0-350 kHz range, this outputs 51 mean values where each of them corresponds to a certain 7 kHz range.
10. We selected 0.98 as a threshold value and checked each of the mean values to see if there is a frequency range that falls below this threshold. In coherence, 1 represents 100 % similarity and we selected 98 % as threshold to give a small error space and this number worked well with our tests. We also selected 0.95 as the “risky” threshold that means there is a high chance of a failure or an error. Any value that is smaller than this 0.95 threshold is considered to be a failure. Please refer to the results & discussion section to see some experiments and results.
11. After we calculate the mean values for 7kHz intervals of 0-350 kHz range, our algorithm repeats itself starting from step 4 and moving on with the new data sector.

4. LITERATURE RESEARCH RELATED TO GRINDING PROCESS ERRORS

Grinding is a widespread production process and has long been a fixed part of almost every industrial production environment. During grinding, the parts (workpieces) are literally given the “final polish”. Grinding operations thus contribute greatly to the quality of the finished workpiece. However, problems can often occur during the grinding process.

Grinding uses the abrasive on the grinding wheel to remove material from the workpiece, so wheel selection greatly influences the process. Factors like the abrasive, the bond holding it to the wheel and the density of the abrasive all affect the grinding process. But the process chain can also include the coolant, the dressing tool, the workpiece material, the grinding machine, the grinding parameters and the work holding. The weakest link in the process sets the limit of the process capability.

Grinding Forces

To detect grinding problems, a person must first understand the forces involved in the grinding process. As shown in Figure, chip removal involves both a tangential force as the wheel cuts (Ft) and the normal downward force (Fn) At the same time, the wheel rotation is exerting force (Vc), and the workpiece is creating a force as it moves along an axis (Vw). These forces and the links in the grinding process can lead to geometric grinding errors, such as dimensional or positional deviations, and physical or chemical errors, such as unwanted changes in the material characteristics of the workpiece's surface. These errors should lead an operator to examine the grinding process to determine their sources. An operator should ask: Do the feeds or speeds need to be adjusted? Was the correct grinding wheel chosen? Was it dressed correctly? Is the coolant clean? Is the grinding machine set up correctly for the workpiece? To answer some of these questions, look at the workpiece. Its ground surface texture should be consistent with a silky gloss. Marks, commas or scratches should not be visible.

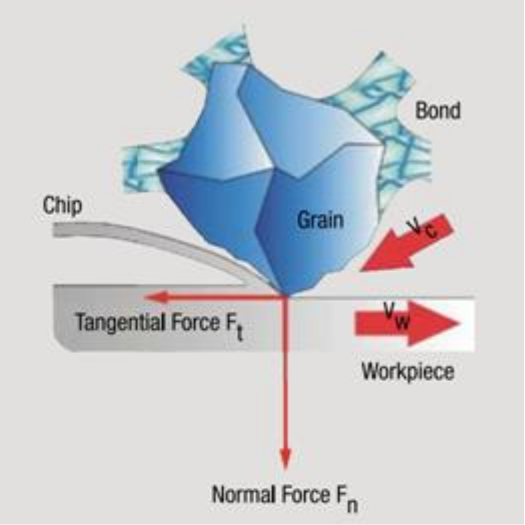


Figure 11 The forces in the grinding process

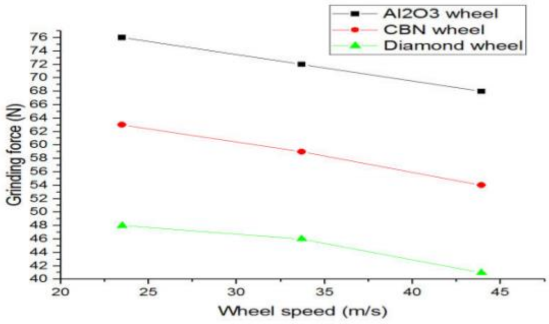


Figure 12 Wheel speed vs Grinding Force

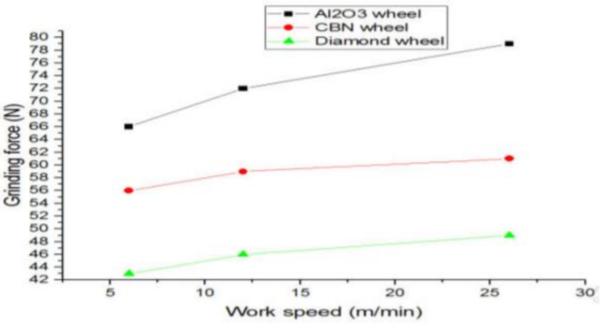


Figure 13 Work speed vs Grinding Force

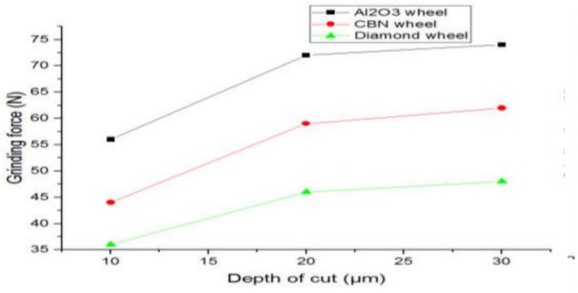


Figure 14 Depth of Cut vs Grinding Force

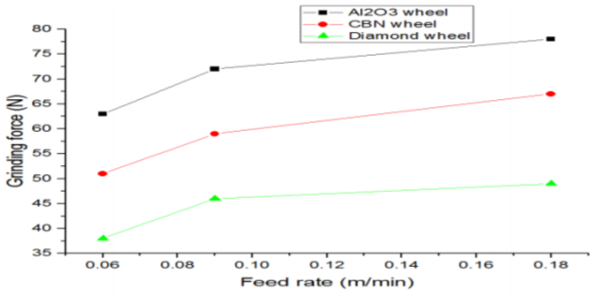


Figure 15 Feed Rate vs Grinding Force

In the research paper (Mahamani & Jawahar, 2018), the effect of wheel speed on grinding force as a function of wheel materials is shown in Figure 12. This investigation is carried out by fixing the work speed as 12m/min, depth of cut 20µm, feed rate 0.09m/min and 5% reinforcement ratio. It is seen from Figure 12 the diamond wheel performed better than other wheels in terms of generating very low grinding force.

Al2O3 wheel generates higher grinding force for the given experimental conditions. It also is seen from the Figure 13 increase in wheel speed decrease in grinding force. The grinding force increases with an increase in workpiece speed and depth of cut as in the figures. Higher force ratio always corresponds to severe tool wear; therefore, low tool sharpness in the super-high-speed grinding process. Diamond gives lesser grinding force and better surface finish compared to SiC wheel.

The effect of work speed on grinding force as a function of wheel materials are shown in Figure 13. This investigation is carried out by fixing the wheel speed as 33.7m/s, depth of cut 20µm, feed rate 0.09m/min and 5% reinforcement ratio. It is seen from Figure 13, the diamond wheel performed better than other wheels in terms of generating very low grinding force. Al2O3 wheel generates higher grinding force for the given experimental conditions. It also is seen from the Figure 13 increase in work speed increase in grinding force.

When the workpiece speed increases, the moving speed of the grinding source is increasing. So, the heat source works little time on the workpiece and a large amount of grinding heat transfers quickly into the atmosphere. Increasing workpiece speed and grinding depth result in the increase of the maximum undeformed chip thickness and grinding force. Both the normal and the tangential components of the grinding force show moderate increases with increasing workpiece speed. Therefore, the grinding force is inversely related to the material hardness, topography after machining non-reinforced Al and AI-SiC composites.

The effect of depth of cut on grinding force as a function of wheel materials is shown in Figure 14. This investigation is carried out by fixing the wheel speed as 33.7m/s, work speed as 12m/min, feed rate 0.09m/min and 5% reinforcement ratio. The diamond wheel performed better than other wheels in terms of generating very low grinding force as we can see in Figure 14. Al2O3 wheel generates higher grinding force for the given experimental conditions.

It also is seen from the Figure 14 increase in Depth of cut causes an increase in grinding force. As the grinding wheel velocity increases, the heat generated in the deformation zone increases and thereby softening the aluminum matrix thus reducing the force required to remove the material, the surface roughness decreases with an increase in wheel velocity and workpiece velocity. This is due to the increase in relative velocity between the wheel and workpiece and the reduction in contact time thereby reducing the chip thickness, tangential grinding force and surface roughness increase with an increase in feed and depth of cut, increase in material removal rate and the increase in chip thickness account for the increase of the tangential force (FT), increase with an increase of percentage of SiC volume fraction.

The effect of feed rate on grinding force as a function of wheel materials are shown in Figure 15. This investigation is carried out by fixing the wheel speed as 33.7m/s, work speed as 12m/min, depth of cut 20μm, and 5% reinforcement ratio. It is seen from Figure 15 the diamond wheel performed better than other wheels in terms of generating very low grinding force. Al2O3 wheel generates higher grinding force for the given experimental conditions. It also is seen from the Figure 15 increase in Feed rate increase in grinding force. The relative velocity between the wheel and the workpiece and the reduction in contact time reduces the chip thickness.

Speed Effect on Grinding Temperature

In a high-speed grinding process, the increased grinding velocity will greatly reduce the undeformed chip thickness and thus a reduction of grinding force. However, increase of grinding wheel velocity will cause a substantial increase of grinding power, which will produce more heat.

In the research paper that is written by Chongjun Wu (Li, YaNG, Lyang, 2017), the different temperature characteristics in high-speed grinding of typical brittle materials and ceramics are discussed in detail. The results displayed that the grinding temperature for different materials differs a lot. According to the experiments, for the SiC, when the wheel speed is below 80m/s, the temperature rises and when it is higher than 80m/s the temperature goes down. However, the TC4 shows a linear increase all the way with the increase of wheel speed. We learned that it is more because SiC has a higher heat dissipation rate and stronger deformation resistance. Moreover, coolants help to reduce about 30% of grinding temperature for SiC grinding. To achieve a higher material removal rate, the increase of the worktable speed brings out a lower temperature for the increase of heat transfer rate into the air. As a result, it is suggested that a fast shallow grinding helps to reduce both SiC and TC4 to suppress a higher temperature.

Physical and Chemical

Roundness or concentricity issues take more analysis and patience. The workpiece centers should be checked for nicks, burrs, dirt and pre machining accuracy. The ideal center is within 0.0002" roundness, is not oval and has no burrs or nicks. Small deviations are acceptable if they are within tolerances and concentrically distributed. The most apparent problems are when the deviations become unbalanced, and the round becomes an oval. Such problems can occur if the workpiece moves in the work head or tailstock centers when the grinding wheel is touching it. Cleaning the center with a center-hole sharpening wheel can sometimes be the answer to this problem. However, deviations or out-of-roundness errors may be so large that some workpieces cannot be salvaged and must be scrapped.

Achieving workpiece straightness is a second geometric challenge. One unwanted outcome is a larger diameter in the middle of the workpiece than on the ends. Possible causes include:

- Bending forces during the grinding process,
- Incorrect infeed, and incorrect wheel overlapping,

- Too much coolant pressure on the workpiece (especially when working with thin parts),
- Tailstock or work head misalignment, or
- Dressing issues, such as when the wheel is not sharp and requires too much grinding force.

Coolant

Coolant plays a large part in proper grinding, and the wrong coolant or improper coolant application can cause various problems.

Grinding processes must be cooled due to process heat being generated through friction and chip removal. To achieve this, coolant lubricant (oil or emulsion) is used which is introduced into the machining zone via nozzles. There, the coolant lubricant cools the process and reduces the friction between the workpiece and tool. coolant lubricant may also perform other tasks within the machine tool (e.g. cleaning the grinding wheel, bed flushing). Due to process cooling, higher cutting speeds and feeds are possible, and the grinding process is rendered more stable, ideally without grinding burn. After use, the coolant lubricant must be processed. This includes the filtration and cooling of the coolant lubricant.

There are several types of coolants, we can list some of them that are used in one of the research papers (Mahata, S, 2011): cutting oils, water, soluble oil, solid or semisolid lubricant and lastly cryogenic cutting fluid. Different types of coolants with varying and diverse compositions are used for grinding different types of work material in order to reduce the heat generated due to friction and to carry away the heat produced as well as for efficient swarf disposal.

Grinding Wheel Design

Abrasive: It is important that hardness in abrasives is retained at high temperatures and that the abrasive does not react chemically or diffuse too readily into the workpiece material.

Hardness in most abrasives reduces with temperature. Thermal properties of abrasive grains are important for abrasive wear resistance and grinding temperatures. False use of abrasives may cause errors.

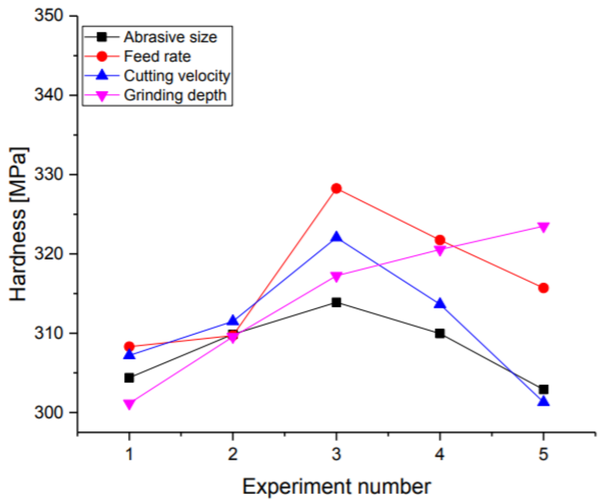


Figure 16 Effect of grinding parameters on hardness

The figure 16, presents the change of hardness with different grinding parameters. As can be seen from the Fig, the hardness changes within a small range with increasing grinding parameters. Hardness is the most sensitive to the change of grinding depth which is caused by cutting forces which are significantly affected by grinding depth. With increasing of grinding depth, the loads for each abrasive increases and abrasive wear aggravates, which leads to the significant increase of cutting force, thus, surface hardness increases

Wheel bonds: There are 3 main wheel bond types; organic, metal and vitrified bond wheels. The main function of bonding material is to hold the grains together which varies in strength, elasticity etc. The wrong usage of the bonding material for abrasives may cause problems.

Wheel mounting: It is a crucial process because each part has several purposes such as balancing, avoiding stresses, friction to accelerate, brake and overcome grinding forces. Wrong manufacturing of the wheel may cause errors.

Wheel wear: During the lifetime of a grinding wheel, the tool wear is one of the significant factors that specifies the quality of completed surfaces in the manufacturing process. For instance, wear of grinding wheels might cause dimensional errors and product deformation due to abnormal cutting temperatures. If a grinding wheel wears too slowly, the abrasive grains then become blunt, so that grinding forces increase, size errors increase, temperature rise increases, and there is an increased risk of thermal damage to the workpiece. To avoid these problems, in conventional solutions, the grinding wheels are replaced or re-dressed repeatedly (continuously). However, replacing and re-dressing operation requires to stop the machine completely, and consequently may have an impact on production time and efficiency.

In case of continuous dressing the grinding wheel is getting regenerated simultaneously which allows steady sharp cutting edges and high cutting power. Thus, one of the most significant applications is in creep feed grinding of super alloys, especially for turbine blades.

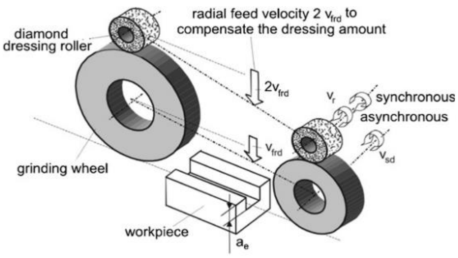


Figure 17 Depth of dressing cut during continuous dressing

Thermal Damage

Abrasive properties, depth of cut, grain sharpness, grinding fluid, high removal rate grinding, wheel wear, work material have effects on the temperature, thus thermal damage.

Burn: One of the biggest and most known problems is **grinding burn**, which is thermal damage to the rim zone of the part. Grinding burn occurs when too much heat is channeled into the part. Microcracks and brittle surfaces are often the result. The occurrence of grinding burn depends on several factors and the interactions thereof. The most frequent problems during grinding include:

Insufficient cooling during grinding: Prevention from thermal damage is achieved via targeted coolant lubricant supply to the machining zone. If the coolant lubricant does not enter 100 % into the machining zone, it takes up less process heat and grinding burn may occur.

Overly high infeed: When grinding parts (workpieces), the process generates a great deal of heat, which is ideally led away with the chips and the coolant lubricant. However, it is impossible to avoid some of the heat entering the part. If the heat input into the part is not too great, this poses no problems to the production process. However, if the infeed is too high during grinding and there is insufficient cooling, such a great amount of heat enters the part that grinding burn occurs. Other wrongly selected process parameters may also have the same effect during part machining.

Grinding with too little coolant lubricant: It is essential to ensure an adequate coolant lubricant supply to the machining zone. A large proportion of the waste process heat is bound and transported away in the coolant lubricant. Only part of the heat generated is taken up by the part, thereby lowering the risk of grinding burn considerably. Frequently, coolant lubricant is used generously in machine tools to achieve a process with zero grinding burn. However, even massive use of coolant lubricant will not succeed in preventing grinding burn if it is unable to reach the machining site in a targeted way and at the right exit speed.

Grinding wheel loading: If a grinding wheel is highly loaded, the pore spaces become clogged. This means that the grinding wheel can then no longer transport any coolant lubricant and removed chips are no longer led away reliably from the machining site.

Work Speed: A low work speed may cause a burn.

Surface Crack: Heating is accompanied by thermal expansion and contraction. As the wheel passes a point on the workpiece, the surface expands. After the wheel has passed, the surface rapidly cools and is quenched by the bulk material. At this stage, the material contracts. If the thermal expansion is sufficient, the subsequent cooling contraction may lead to cracking.

Vibration Problem

Vibrations in grinding lead to surface waviness and loss of workpiece accuracy. Wheel wear is increased, and workpiece roughness deteriorates. Three types of vibration that cause damage are;

- Impulsive vibrations
- Forced cyclic vibrations
- Self-excited regenerative vibrations.

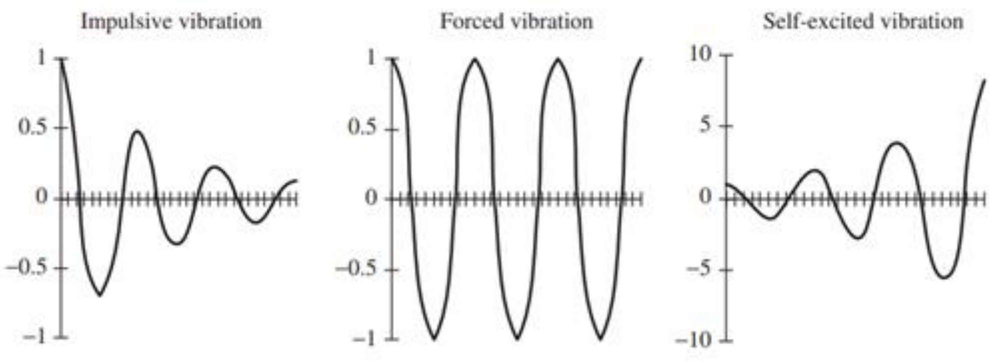


Figure 18 Impulsive, forced, and self-excited vibrations (amplitude vs time)

Figure shows an example of a steady sustained vibration. Sources of steady vibration include wheel unbalance, rotary dresser unbalance, spindle unbalance, motor unbalance and pulley wheel unbalance. The source of the problem is usually identified from the vibration frequency. The vibration frequency can be identified from the wavelength of the waves on the workpiece surface and the work speed.

Impulsive vibrations are a special case of forced vibration where the forcing is a sharp disturbance or shock loading that arises either from outside the machine or from within the machine. For example, shock loading occurs when a worktable is fed up to a stop and suddenly halted. This situation often arises in plunge feed operations where the infeed is fed rapidly to a stop and then held there to spark out. Other sources of apparently random vibrations can be flapping belts, backlash in feed-drives, damaged lead screws, gears and slide-ways. Random vibrations can also arise externally from a passing heavy machine or truck or from goods dropped nearby on the floor.

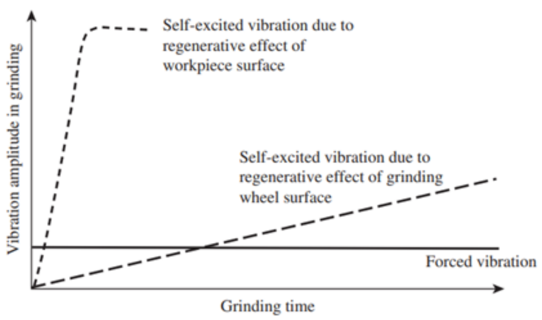


Figure 19 Growth of self-excited vibrations and forced vibrations

Regenerative self-excited vibrations occur in most machining operations as a consequence of machine vibration interacting with depth of cut. Self-excited vibrations build up with time. This is therefore the most serious cause of inaccuracy in grinding. Self-excited vibrations can build up in two different ways as either work-regenerative chatter or as wheel-regenerative chatter.

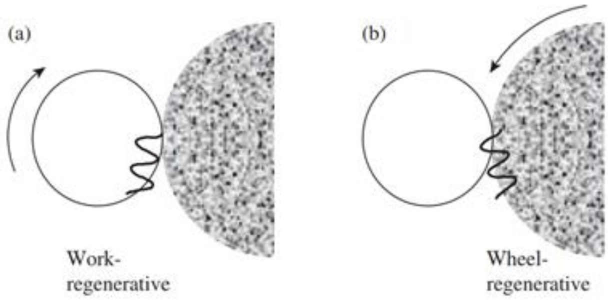


Figure 20 (a) Work-regenerative and (b) wheel-regenerative vibrations

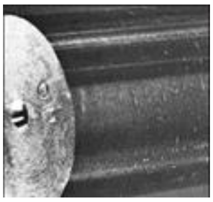
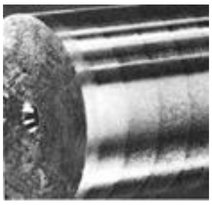
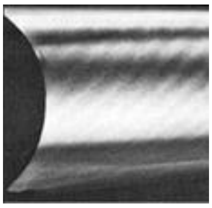
Work-Regenerative Vibration: Vibration starts from a small amplitude and builds up afresh on each workpiece surface as grinding proceeds. Waves generated on the workpiece surface result in a change of depth of cut after one revolution of the workpiece. This causes a new wave to be created. The phase shift between the old and the new surface waves creates a varying depth of cut. The process becomes unstable when the phase is right, and the grinding force is too large. The vibration usually develops very quickly but the amplitude of vibration is ultimately limited by non-linearity such as loss of contact between the workpiece and the grinding wheel or by interference due to the shape of the grinding wheel.

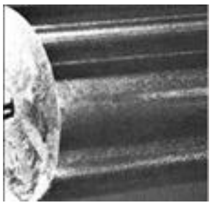
Wheel-Regenerative Vibration: Wheel-regenerative vibrations build up progressively from one part to another. The amplitude continually builds up on the surface of the grinding wheel and becomes larger for each workpiece produced. Eventually, the wheel surface is so badly affected that the wheel has to be redressed to restore accuracy and acceptable surface roughness.

Vibration behavior in cylindrical, internal and surface grinding processes differs in significant ways. In the case of internal grinding, the chatter frequency is, in most cases, related to the natural frequency of the grinding wheel spindle system because the dynamic stiffness of internal grinding spindles is often lower than that of the workpiece system. For cylindrical grinding, the dynamic stiffness of the workpiece system is usually lower than that of the grinding wheel spindle system. In surface grinding, chatter vibration caused by the regenerative effect on the workpiece surface develops in a less constrained way. This is because the phase shift between the new wave and the old wave on the surface is not constrained because of uncertainty in the workpiece reciprocating motions.

Some Error Examples with Illustrations

In many cases, a grinding error has more than one cause. Here are some possible causes (one or multiple) that may lead to visible grinding errors on the surface which we may detect with the acoustic emission sensor by searching for some signal patterns.

Illustrations	Visible Errors	Possible Cause(s)
	Surface shows irregular, short "comma" scratches.	Abrasive grains in the coolant.
	Surface shows chatter marks that are distributed over the entire circumference and lie parallel to the workpiece axis.	1) Wheel not properly balanced. 2) Vibrations from an outside source. 3) Qs (wheel-to-workpiece speed ratio) too low.
	Burning marks: Helical marks or local yellowish/ brownish discoloration of the surface.	1) Overheating in the grinding process. 2) Insufficient coolant supply. 3) Wheel too finely dressed. 4) Wheel too hard.
	Grinding with angular marks.	A grinding wheel has been dressed too fast and transfers the error onto the part.

	Grinding with source interference: Surface shows marks parallel to the workpiece axis that are on part or all of the workpiece circumference	1) External influences, such as a forklift driving by or a punch press near the machine. 2) A ventilator fan or centrifuge may also be a cause; if so, the bevels will be spread over the entire workpiece.

5. DEVELOPMENT OF FAILED DATA

As discussed before, we were not able to conduct our own custom experiments due to the pandemic situation. However, we decided to simulate or create our own fail data using the analysis from our original dataset and literature research since we also need Acoustic Emission Data of failed grinding processes.

We want to see the effect of every feature on the signal output of acoustic emission sensors. So we created 4 fail data (explaining 4 features from the given dataset), comparing 2 data with only the difference of one feature to see the effect of that precise feature. We used our literature research to extract meaningful fail data.

Coolant Effect: There can be observed various problems with coolant parameters. Due to the malfunction of coolant, the machine can stop or increase or decrease the level of liquid given to the system. As discussed in the ‘Coolant’ and ‘Thermal Damage’ parts, there can be malfunctions or unexpected changes due to other factors rather than coolant lubricant which may not be efficient or too much for the system to work for the intended results.

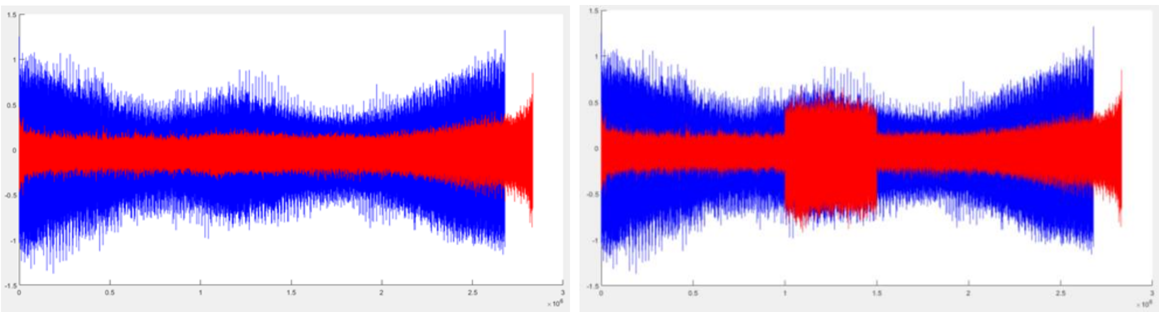


Figure 21 Blue ‘Test 13 (Coolant off)’ - Red ‘Test 21 (Coolant on)’

Test 13 and Test 21 have the same parameter values (feed rate, wheel speed, depth of cut, sampling rate) except the coolant factor. We can observe that with no use of coolant, the acoustic emission sensor detects much more noise. Left graph is the initial data that was provided to us. In order to test the system, we tried to make a realistic change in Test 21(red) as if there was a problem with the coolant for some time which you may see in the right graph.

```
                    % TEST 13 VE TEST 21 (Coolant off-on)

% load test13.mat;
% load test21.mat;
%
% t13= smoothenedAE(test13);
% t21=smoothenedAE(test21);
%
% oran = mean(abs(t13)) / mean(abs(t21));
%
% start= t21(1:1000000);
% temp= t21(1000000:1500000);
% temp = temp.*oran;
% endd = t21(1500000:end);
% FailData_t21 = [start temp endd];
%
% hold on;
% plot(t13,'b');
% plot(FailData_t21,'r');
% hold off;
```

This figure shows the implementation of failed data for coolant off-on. After smoothing the data, we calculated the proportion value by dividing both mean values of 2 different tests. Then, by deciding the interval, we multiplied that part by the proportion value to observe the difference when we use the coherence algorithm.

Wheel: There are various kinds of wheels and its abrasives, wear, bonds etc. When we experiment with the same parameters but different kind of wheels, we expect to get different results. Also, some wrong adjustments due to wheel speed(rpm) may cause problems which we discussed in the 'Grinding Forces' part.

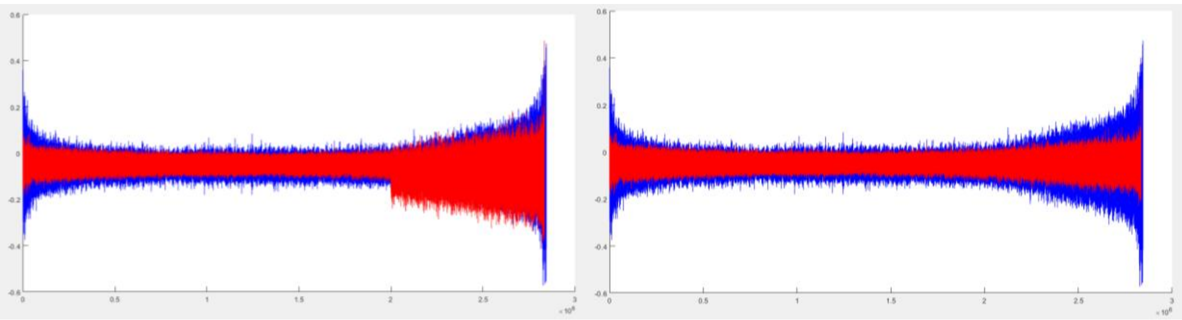


Figure 22 Blue 'Test 17 (Wheel Speed:1500 RPM)' - Red 'Test 20 (Wheel Speed: 1000 RPM)'

In the project, we only experimented with the same wheel in all tests. Therefore, we can only examine the wheel speed effect of one type of wheel material. Test 17 and Test 20 have the same parameter values (feed rate, coolant situation, depth of cut, sampling rate) except the wheel speed. We can observe that, with more wheel speed, the acoustic emission sensor detects much more noise. Left graph is the initial data that was provided to us. In order to test the system, we tried to make a realistic change in Test 20 (red) as if a contingency happened after some time, or an operator made a change which you can see the sensor data change in the right graph.

Feed Rate (mm/min): The effects of change in feed rate are discussed in 'Grinding Forces', we know that the increase in feed rate will result in a decrease in the time spent on the grinding process.

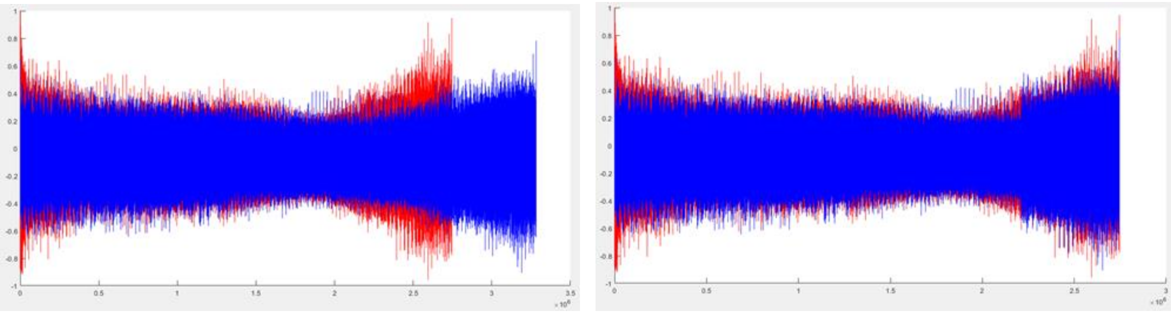


Figure 23 Blue 'Test 8 (Feed Rate: 800 mm/min)' - Red 'Test 6 (Feed Rate: 1200 mm/min)'

Test 6 and Test 8 have the same parameter values (depth of cut, wheel speed, coolant condition, sampling rate) except the feed rate. We can observe that, the larger the feed rate is, the smaller the time in the grinding process gets. Left graph is the initial data that was provided to us. In order to test the system, we tried to make a realistic change in Test 8, as if something unexpected happened and it shortened the time of the grinding which should have lasted longer with the given parameters, or the operator made a change.

Depth of Cut (microns): As discussed in 'Grinding Forces' part, the increase in depth of cut will result in the increase of removed material. Wrong adjustments or unexpected changes due to wheel speed, work speed, chip thickness etc. may change the depth of cut of the workpiece thereby affecting the material removing with unwanted rates.

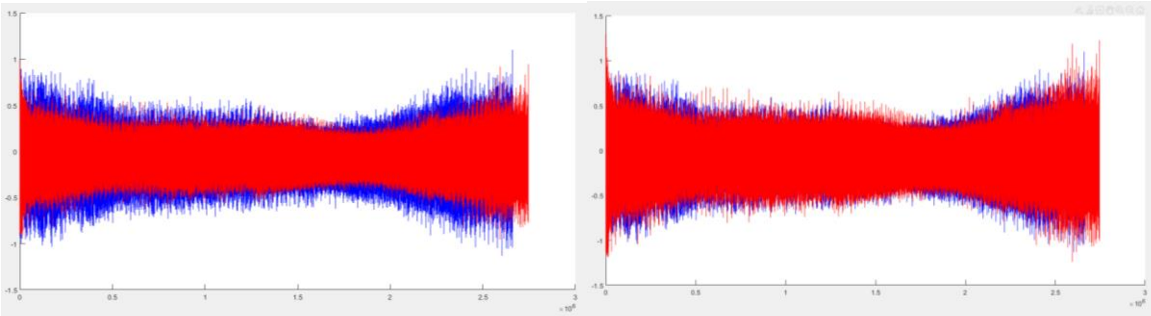


Figure 24 Blue 'Test 11 (Depth of cut: 8 micron)' - Red 'Test 6 (Depth of cut: 2 micron)'

Test 6 and Test 11 have the same parameter values (feed rate, wheel speed, coolant condition, sampling rate) except the depth of cut. We can observe that, with more depth of cut, the acoustic emission sensor detects much more noise. Left graph is the initial data that was provided to us. To test the system, we tried to make a realistic change in Test 6 (red) as if something was already wrong from the beginning of that experiment and the sensor data of test 6 came out completely different than the expected.

6. RESULTS & DISCUSSION

We have explained how we developed the methodologies for signal preprocessing and how we analyzed the grinding processes. Finally, we conducted experiments with the failure data that we extracted, using the algorithm that was explained in the above parts. The results and analyzes from the experiments are explained below.

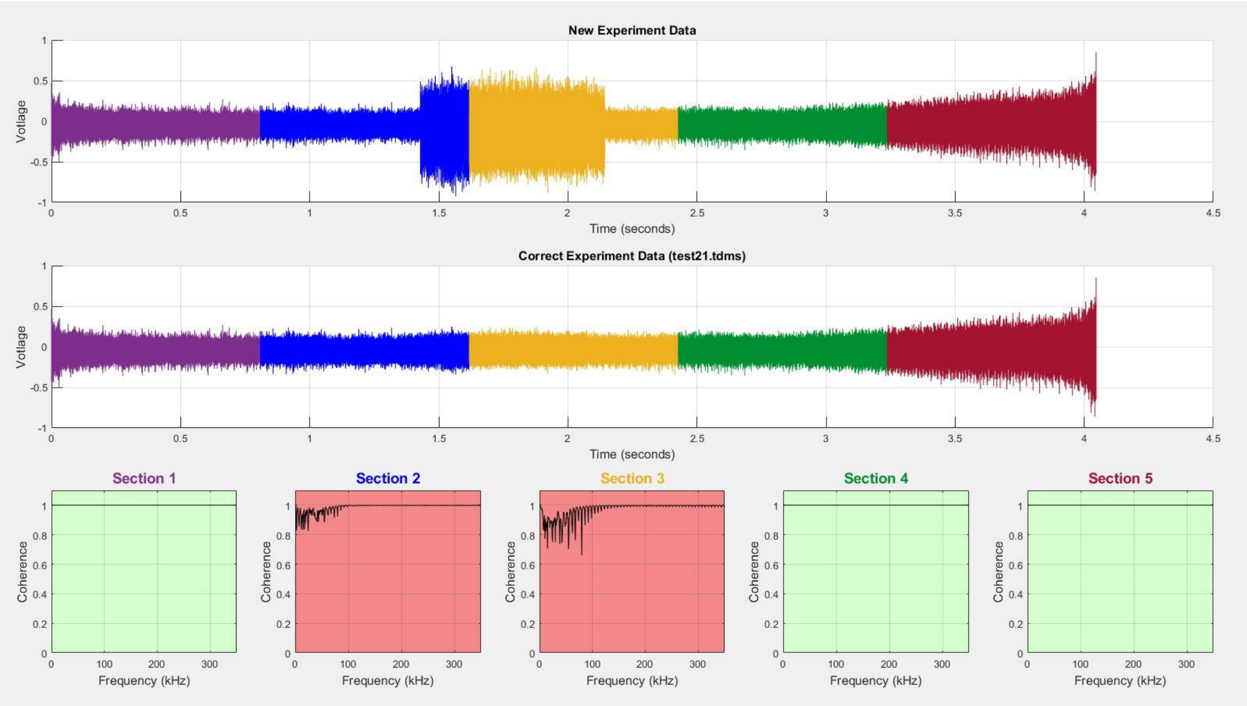


Figure 25 Experiment data for the coolant effect

This figure is the experiment data for the coolant effect that is explained in the above parts. The upper data is the failed data, below is the original (correct) data that the algorithm extracted from the database. Blue and yellow parts correspond to Section 2 and Section 3 where an error occurred according to the change in the frequency levels.

This coherence estimation methodology gives us what we want in this example of data. It shows in which section did the error occur. However, frequency cannot be used for all the monitoring processes because it does not show all the errors.

As seen in the example below, in the failed data, there has been a change in green and red parts, therefore we expect to see an error in Section 4 and Section 5. However, it does not show an error in Section 5. This indicates that the coherence estimation is not always accurate to determine the changes in the data since it does not detect the change in amplitude levels.

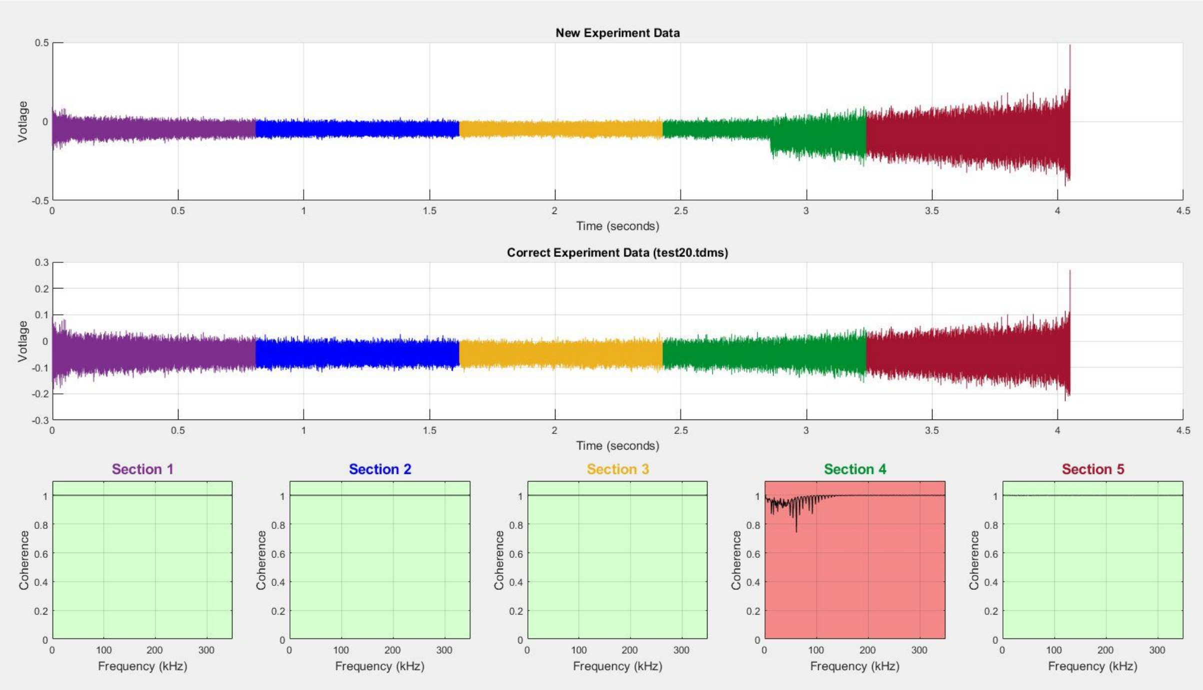


Figure 26 The failed data

We see the same problem in the following experiment as well. It is conducted to see the depth of cut change. Failed data details can be found in above parts. There has been a change in the whole data, but we cannot see the difference by using the coherence algorithm that we developed. It is not effective to demonstrate the change in amplitude levels.

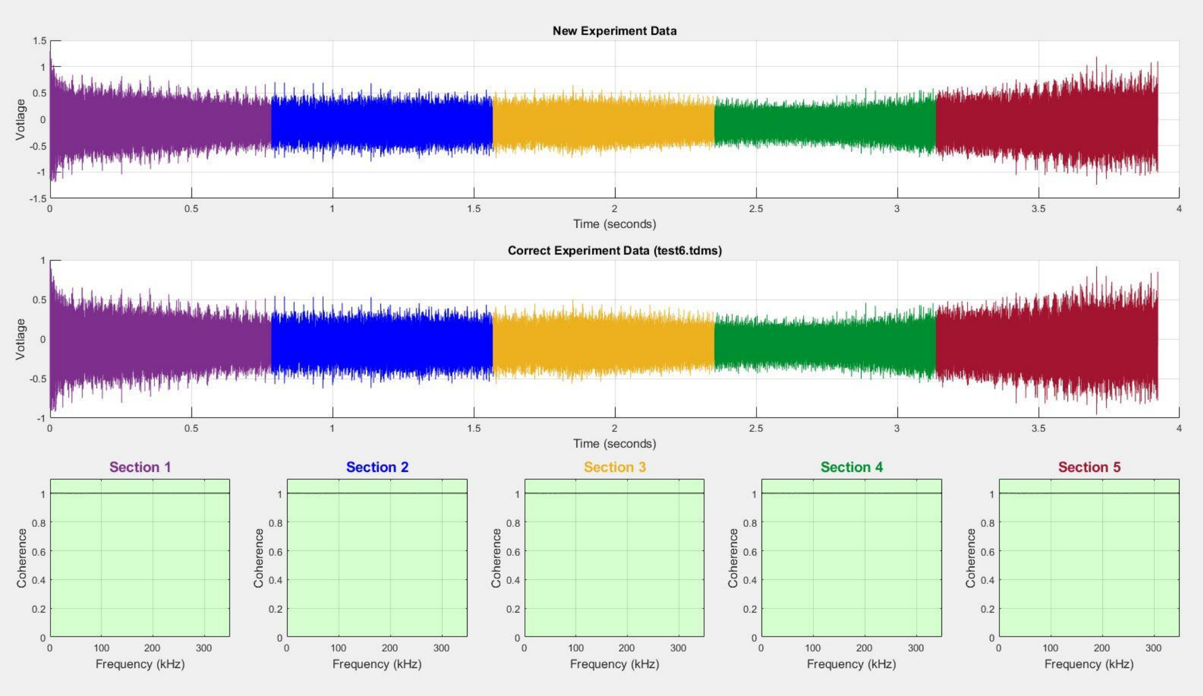


Figure 27 experiment data for the depth of cut change

Below experiment is conducted to see the change in feed rate. Details can be found in the ‘Development of Failed Data’ part. Failed data is extracted by shortening the data. Here we are expected to see an error only in the last sections however it shows risky in Section 1 and errors in all other sections. This is because in the algorithm it divides the data into sections in 5 levels. Since we shortened the data, the sections are not matched between the failed and original data, therefore showing errors in all sections.

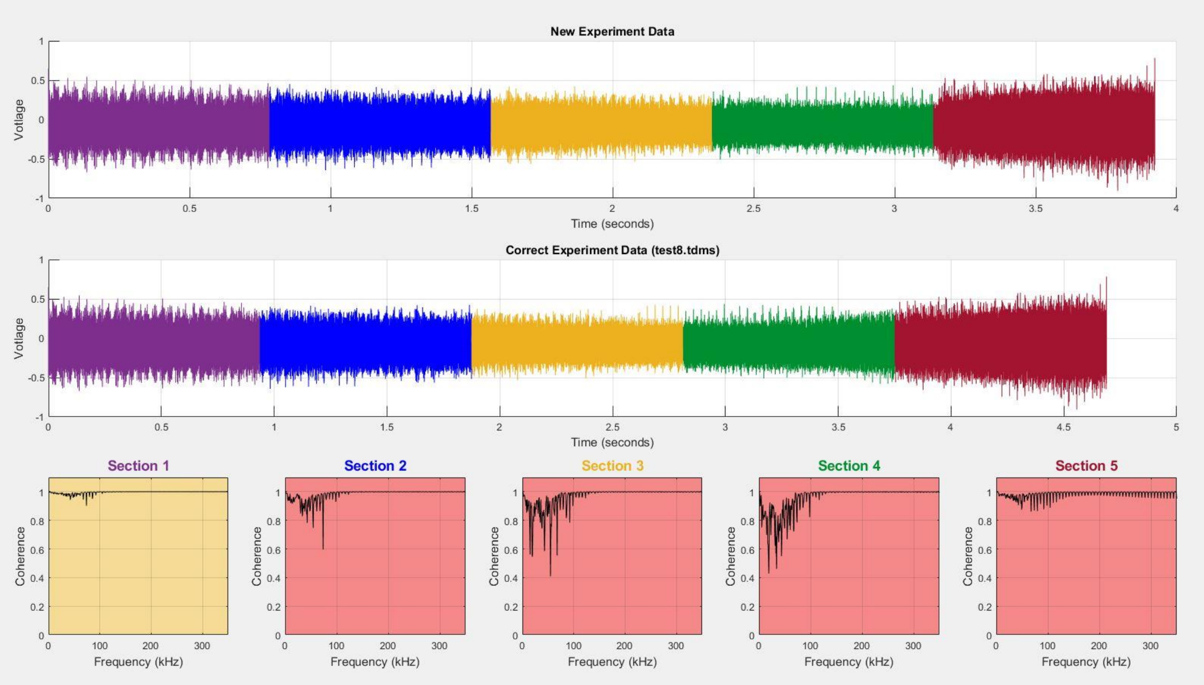


Figure 28 Experiment data for the feed rate change

The discussion of these experiments and coherence estimation methodology is explained in the following Conclusion part.

7. CONCLUSION

By the coherence algorithm that we had developed, we can only detect that there is a significant difference that needs to be controlled related to the process. Since we created our own failed data by manipulating it, we had the information about the reason behind the difference in the process. For example, we expected a change when we closed the coolant for a while, and the result turned the way we predicted. However, in real life circumstances, Acoustic Emission Sensors are known as quite sensitive to most of the things that we can imagine. Therefore, indeed we are able to monitor the unexpected variations or faults at frequency level, but still have a long path to identify the reason behind the changes. As a result, we can have an insight into whether there was a problem during the process by looking at the frequency coherence differences.

We cannot claim that the project is complete for industrial usage since it still needs some adjustments and more data to progress further. However, we successfully experimented on various methodologies and implemented different algorithms to manipulate the data we received. For sure, circumstances were not convenient during the pandemic and because we had limited data and not being able to conduct more experiments ourselves. But we still managed to come up with a good solution & algorithm even with the limited data we have. We partially solved this issue by creating our own failure data using the data we have and with literature research.

During our project period, we were planning to create a machine learning model to solve this problem and we have been working on the data to extract various features to train a model. However, due to lack of experiment data it was not possible to train an accurate model and test it. Therefore, we moved on with a different approach and created our smart algorithm as stated in Appendix 2.

8. RECOMMENDATIONS & FUTURE WORK

Firstly, we would like to thank our supervisor Erhan Budak and our project Assistant Hamid Jamshidi for their support and help during our project. For the future progress of this project, we would like to list some of our recommendations and suggestions:

1. It is crucial to have more and variety of experiment data for such monitoring applications.
2. It would be great if various sensors are also used while doing an experiment rather than just using the AE sensor since as we also discussed in our meetings, AE sensor is not enough for classification of the failures precisely and does not provide comprehensive information about the ongoing operation.
3. We suggest that training a Machine Learning model would be a better solution for this problem. But, as mentioned, it will require a large dataset and it would be even better if there is data from different sensors for the same experiment since more features and data makes Machine Learning models more accurate and reliable.

9. ETHICAL ISSUES

The goal of the project was to monitor the grinding processes and create a chance to remotely control and analyze the processes through the signals coming from the acoustic emission sensor. Grinding operation itself brings some risks such as human body injury, fire, air pollution etc. Remotely controlling these processes will even result in the decrease of human contact with the machine that may cause health and safety problems. Along with the project design, we did not encounter any ethical problems. Throughout the process to the ultimate solution of the problem, no ethical issues are expected to come up.

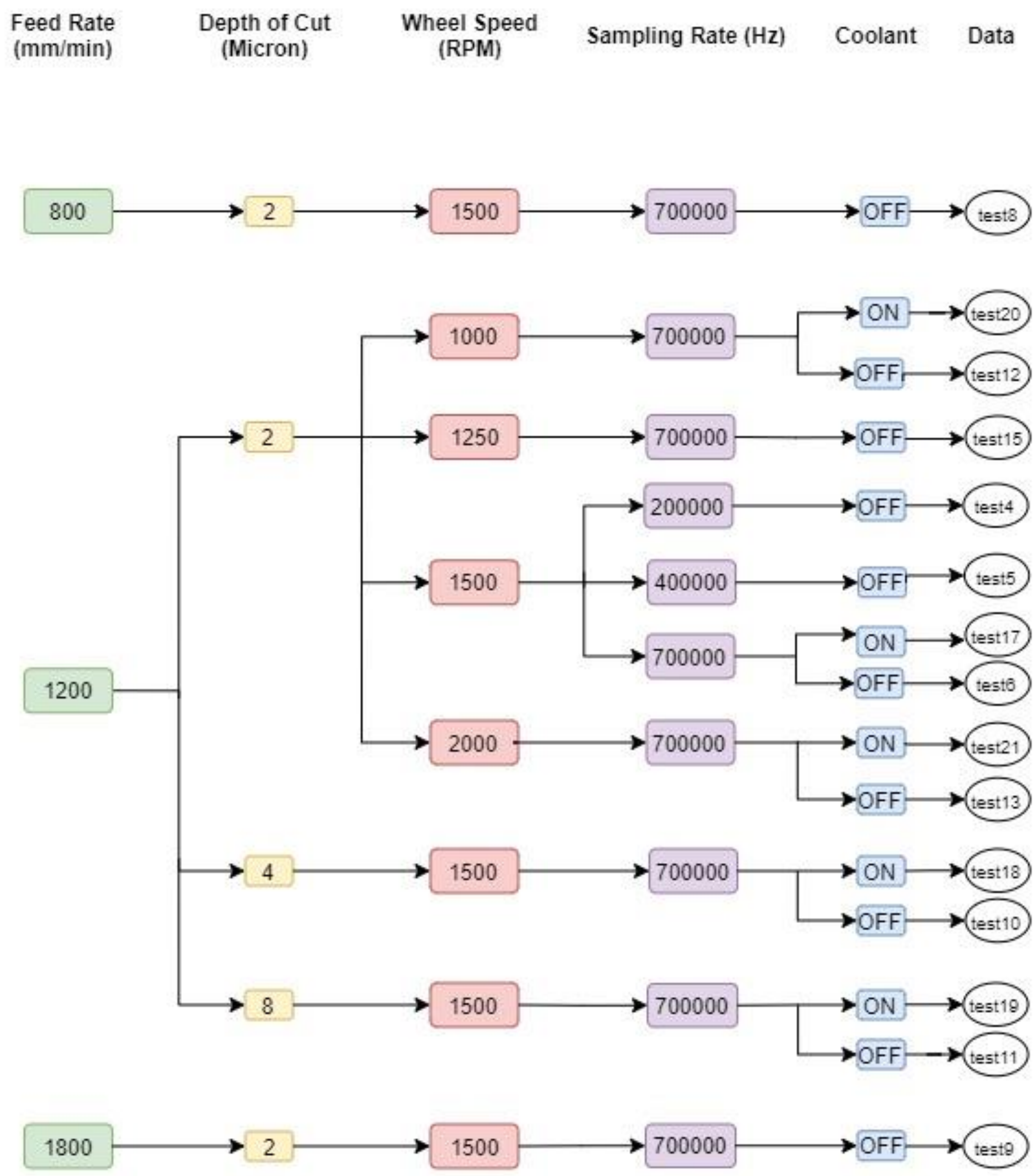
10. PROJECT MANAGEMENT

At the beginning of the project, we were assuming that we would be able to do more experiments and do more tests on data. However, we were not able to do any of these. Therefore, we had to come up with different plans. During the implementation, we dived into more literature research related to the grinding process and AE sensors and how to use them in the most efficient way. We developed several algorithms so that we were able to compare the RMS values of the signal. The data sets that we received as ready were not that complex. However, we did a good job of seeing the effects of the features such as coolant, feed rate, wheel speed on the grinding process.

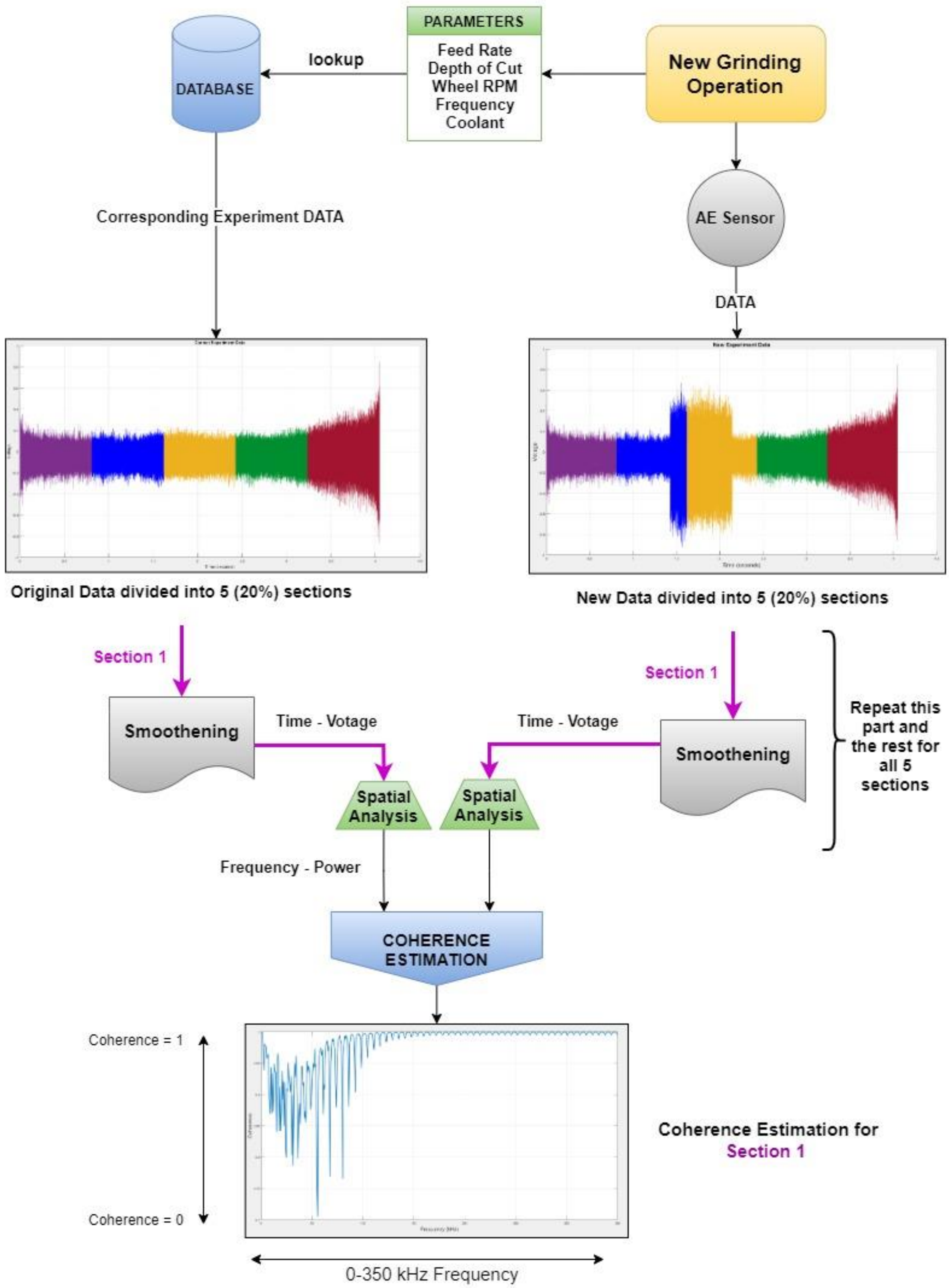
11. APPENDIX

APPENDIX 1

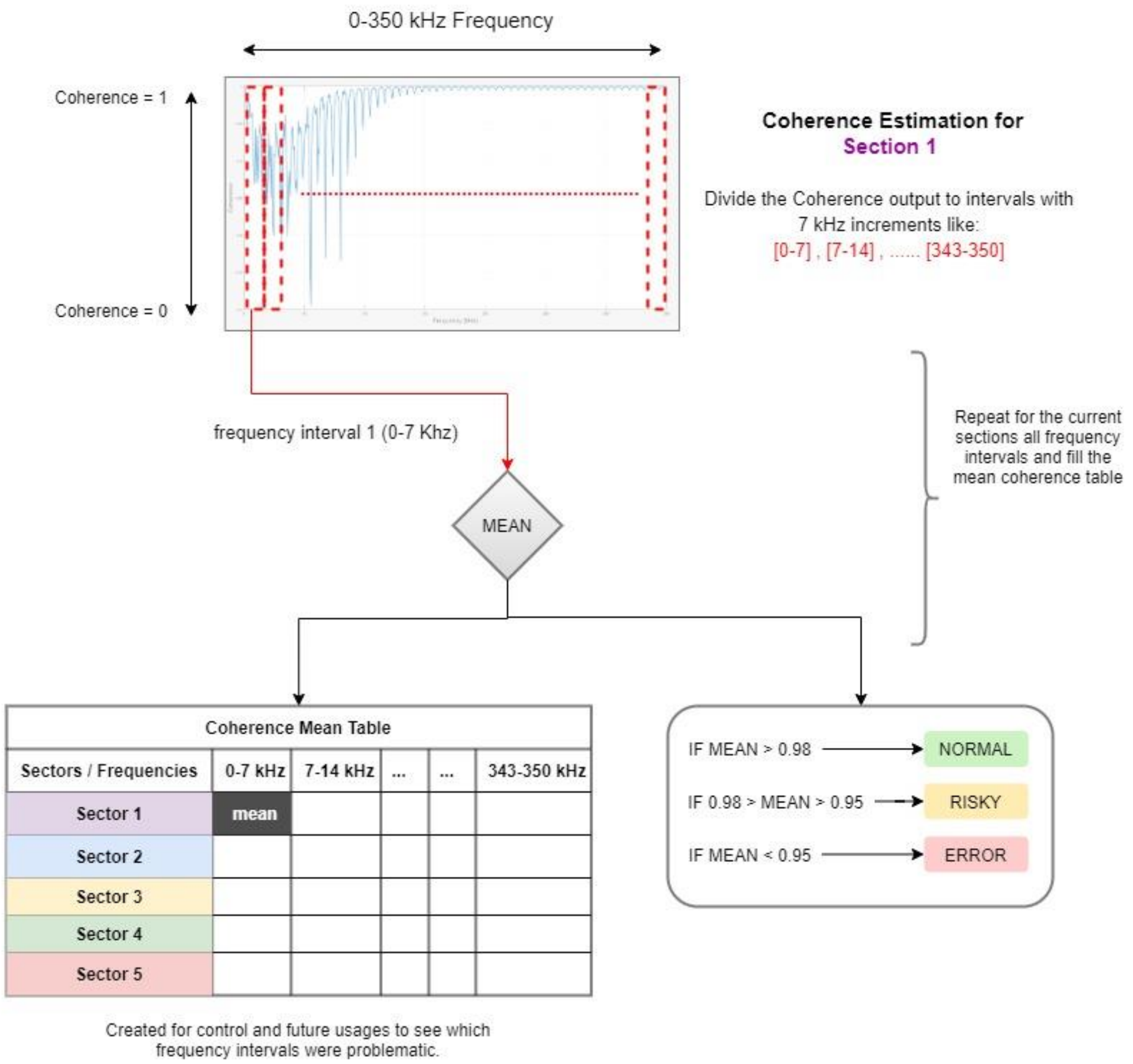
Database structure



APPENDIX 2 PART 1



APPENDIX 2 PART 2



12. REFERENCES

· Richard, J. (2007, December). Grind Right. Cutting Tool Engineering, 59(12).

· Grindaix GmbH. (2021). Frequent Problems During Grinding. Grindaix Magazine.

· Rowe, W. B. (2014). Principles of Modern Grinding Technology (2nd ed.). Elsevier Inc.

· Mahata, S., Mistri, J., Mandal, B., & Das, S. (2011). Coolants and their role in grinding. *Reason-A Technical Journal*, *10*(0), 41.

. Mahamani, A., & Jawahar, S. (2018). Influence of grinding parameters on grinding force and temperature in grinding of AA6061-tib2/ZrB2 in-situ composite. *IOP Conference Series: Materials Science and Engineering*, *390*, 012004.

. Mathworks. (2021). *Analyze signals in the frequency and time-frequency domains - MATLAB pspectrum*. MathWorks - Makers of MATLAB and Simulink - MATLAB & Simulink. https://www.mathworks.com/help/signal/ref/pspectrum.html#d123e133552

. *Cooling during grinding*. (2021, February 17). grindaix GmbH. https://grindaix.de/en/magazine/cooling-during-grinding/

. Jones, J. H. (2018, February 19). *Time series and spectral analysis*. Stanford University. Retrieved May 28, 2021, from https://web.stanford.edu/class/earthsys214/notes/series.html#spectral-analysis

. Wu, C., Li, B., Yang, J., & Liang, S. Y. (2017). Comparison of machining temperature in high speed grinding of metallic materials and brittle materials. *MATEC Web of Conferences*, *114*, 02006.

. Wegener, K., Hoffmeister, H., Karpuschewski, B., Kuster, F., Hahmann, W., & Rabiey, M. (2011). Conditioning and monitoring of grinding wheels. CIRP Annals, 60(2), 757-777.

. Lee, E. T., Fan, Z., & Sencer, B. (2020). Real-time grinding wheel condition monitoring using linear imaging sensor. Procedia Manufacturing, 49, 139-143.

. Lei, P. (2011, February 8). *Spectral Analysis*. A-to-Z Guide to Thermodynamics, Heat & Mass Transfer, and Fluids Engineering Online. Retrieved May 28, 2021, from https://thermopedia.com/content/1141/

. Souza, C. N., Catai, R. E., Aguiar, P. R., Salgado, M. H., & Bianchi, E. C. (2004). Analysis of diametrical wear of grinding wheel and roundness errors in the machining of steel VC 131. Journal of the Brazilian Society of Mechanical Sciences and Engineering, 26(2)