

Failure mode classification for condition-based maintenance in a bearing ring grinding machine

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33 **Abstract**

34 Technical failures in machines are major sources of unplanned downtime in any production and result
35 in reduced efficiency and system reliability. Despite the well established potential of Machine Learning
36 techniques in condition-based maintenance (CBM), the lack of access to failure data in production
37 machines has limited the development of a holistic approach to address machine-level CBM. This
38 paper presents a practical approach for failure mode prediction using multiple sensors installed in a
39 bearing ring grinder for process control as well as condition monitoring. Bearing rings are produced
40 in a set of 7 experimental runs, including 5 frequently occurring production failures in the critical
41 subsystems. An advanced data acquisition setup, implemented for CBM in the grinder, is used to cap-
42 ture information about each individual grinding cycle. The dataset*is pre-processed and segmented
43 into grinding cycle stages before time and frequency domain feature extraction. A sensor ranking
44 algorithm is proposed to optimize feature selection for failure classification and the installation cost.
45 Random forest models, bench-marked as best performing classifiers, are trained in a two-step classi-
46 fication framework. The presence of failure mode is predicted in the first step and the failure mode
47 type is identified in the second step using the same feature set. Defining the feature set in the failure
48 detection step improves the predictor generalization with the classifiers' performance accuracy of 99%
49 on the test dataset. The presented approach demonstrates an efficient failure mode classification by
50 selecting crucial sensors resulting in a cost effective CBM implementation in a bearing ring grinder.

51 **Keywords:** Grinding, Production System, Condition-based maintenance (CBM), Sensor, Failure classification
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1 Introduction

Industrial analytics (IA) and industrial internet of things (IIoT) are key focus areas in many, if not all, manufacturing industries [1]. One of the

¹The dataset will be made available along with the acceptance and publication of this manuscript

more advanced use cases is Condition Monitoring (CM) of machine tools using machine learning (ML) because of the cost benefits associated with it. The effort to adapt to the new and technically advanced ways of working, originating from the concept of Industry 4.0, roots not only from production reliability but also from highly competitive business environment. This has given a great push in development of Information and Communication Technologies (ICT). Hence, the technologies underlying IIoT and Cyber-Physical Systems (CPS) are becoming more prevalent in companies [1, 2]. This has led to increased interest in the industry to adapt Condition based maintenance (CBM) and predictive maintenance (PdM) that can allow for a more deterministic asset availability, increased production reliability and significantly improved maintenance planning [3].

Failure prediction through CM is key in setting up an effective maintenance management system that increases productivity and ensures asset reliability. As part of this maintenance strategy, PdM is achieved through reliably predicting the usability of the asset based on the failure diagnostics, as part of CBM setup, to devise the timely scheduling of maintenance activities [4]. It is, however, challenging to practice CBM in manufacturing industry. The asset to be monitored has to be equipped with sensors and data acquisition system which in itself is not technically easy due to variations in machine design and process needs for specific industry [5, 6].

The aim for any CBM implementation is to propose maintenance decisions based on information acquired through CM [7]. The accuracy in the decision making process reflects the effectiveness of CBM systems [8]. Most popular definition of CBM that exists in the literature [7, 9] signifies the challenges in the areas of *data acquisition*, *data processing* and *decision making* where the CBM implementation and management needs refinement. CBM usually requires the selection of components to be monitored in the asset [10]. Therefore, a considerable investment is required to acquire the right equipment for an appropriate data collection setup. The significant part of the expense comes from the measurement devices, system design, domain knowledge and training [11, 12]. Combination of different methodologies

and techniques for acquiring, managing and analyzing data have to be adopted [13, 14] for accurate decision-making as well as achieving cost effective maintenance planning and execution [5].

To support industry's strive to adapt to changing technology trends and considering the challenges in CBM implementation, the development of comprehensive methodologies in failure diagnostics and prognostic domain providing holistic approach is to be prioritized [15]. Hence to increase the adaptability and integration, there is need for a systematic methodology to be developed to enable implementation of CBM systems [9]. The demand only gets stressed further due to absence of such holistic approaches for PdM applications [16, 17]. The overall lack and limitations of existing CBM implementation procedures creates a space where a lot of confusion between CBM systems and CBM policies have emerged [5].

A lot of research focus has been on such maintenance strategies and techniques including CBM and remaining useful life (RUL) of individual tools and machine subsystems [15]. These works, although significant for CBM and RUL research, has left a large gap in addressing failure modes and performance issues related to machines in production [16]. Despite the inevitable focus on PdM implementation [9], grinding machines and processes are rarely, if at all, part of scientific publications related to CBM and PdM [18]. Industrial grinding processes have come long way in addressing the challenges [19] of process predictability, inventory reduction and need of more automation [20]. However, even today's production grinders struggle to offer precise process predictability due to the complex inter-dependency of process control and the physical and operating condition of the machine [21]. To maintain the quality of the parts produced, the machine needs to be monitored for degradation of its subsystems and components [22]. Given the criticality of grinders in bearing ring production, adapting CBM becomes a crucial choice for maintaining the machines to improve production reliability [23].

Therefore, the aim of this paper is to present an efficient diagnostic framework for failure mode classification as part of a cost effective CBM implementation in a bearing ring grinder. The data acquisition system is designed to acquire the entire grinding cycle along along with the process parameters which form the dataset analysed

here. It is crucial to set up the experimentation so that the failure classes are represented equally in the dataset. A number of experiments are designed and performed which allow the machine to grind parts under different machine conditions to replicate real failures. Various test runs, during experimentation, allow the collection of the data that is used to systematically study the machine behaviour to diagnose failure modes for the machine condition. The data is processed through splitting the grinding cycle into parts in a novel way. The features are extracted and relevant sensors are selected to train failure classifiers for the bearing ring grinder.

2 Method

An experimental approach to failure diagnostics in realizing the CBM framework for bearing a ring grinder has been taken in this article. The CBM framework combines the condition monitoring (CM) and process control by taking advantage of domain knowledge in the proposed methodology. Figure 1 depicts the steps considered in the scope of the work in developing failure mode diagnostics for the CBM. The methodology developed is based on the observations obtained during the machining of bearing rings.

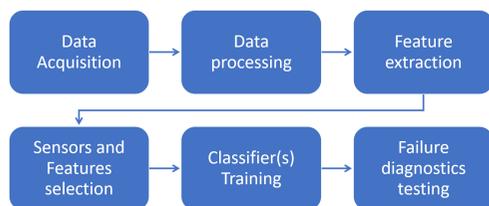


Fig. 1 Failure diagnostic methodology steps in CBM.

2.1 Data Acquisition

The aim to capture and store the data related to sensors and machine's operating parameters are enabled by setting up the machine with dedicated sensors and data acquisition system.

2.1.1 CBM setup

In a production environment a CBM setup needs to be made available that enables predictive maintenance to be tried and developed upon. As

discussed, the challenge not only lies in choosing right methodology to analyse machine data, but also in identifying the best way to monitor the machine and acquire data. The setup has to account for the choice of subsystems and machine components to be monitored and the intended data processing that will be required to develop the diagnostic and prognostic algorithms. Presence of cyber-infrastructure using information and communication technologies (ICT) is crucial in setting up a complete CBM system. Therefore, it has been demonstrated in our work [20] that a functioning and capable system is achievable when a production machine is equipped with sensors for condition monitoring in addition to already existing process control setup. The CBM system has the physical elements and the required infrastructure to support the communication and interaction between different components. The data flow between different parts of the system is presented in figure 2.

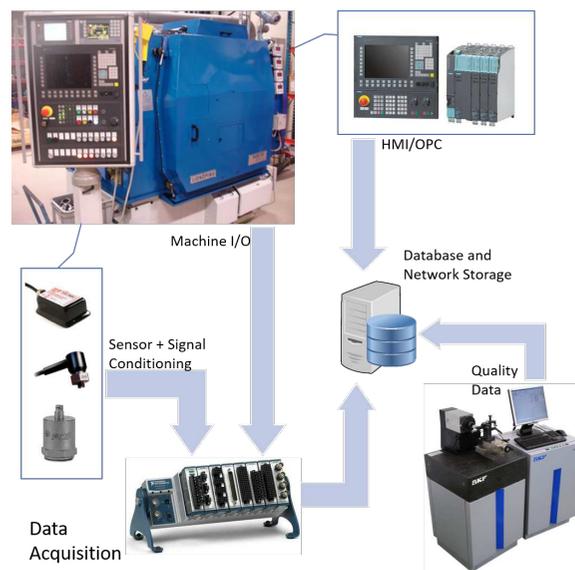


Fig. 2 The data flow setup. Adapted from [20].

The bearing ring grinder, top left in figure 2, is an external grinder *SGB55* from Lidköping and is being used to grind outer rings of bearing type *SKF-6210*. The grinding machine has been equipped with sensors for process control and machine condition watchdogs. The table 1 lists standard sensors and standard systems incorporated in the process cycle recipe used to operate

machine to grind bearing rings during their production. The sensors are mounted on the machine subsystems to measure their respective quantities before and during the grinding cycle. For example, the balancing unit is activated every time the grinding wheel is dressed to ensure a balanced grinding wheel and avoidance of vibrations causing quality issues. Similarly the acoustic emission, force and power sensors are used to monitor and control the cycle itself. The machine's control system is SIEMENS Solution Line series Numerical Controller based system. The process data is captured using OPC server client communication and is published to monitor machine's state and output efficiency in the factory. The data is generated for every grinding cycle in the machine and is pushed into the database.

Table 1 List of sensors installed for process monitoring.

Measured quantity	Sensor	Target subsystem
Force	Kistler 9105C	Workhead
Acoustic emission	Dittel m6000	Grinding spindle
Balancing Unit	Marposs P7	Grinding spindle
Power	Montronix PS100	Elec. motor (grinding)

The additional sensors, listed in table 2 are added to broaden the availability of data for machine, process as well as condition monitoring. The machine and its subsystems, where the sensors are installed, are represented in schematic view in figure 3. The sensors data is acquired in synchronization to machine cycle using National Instruments' (NI) data acquisition hardware where the control and acquisition software is developed in NI LabView platform. The data acquisition system initiates sampling of sensor signals, at 100kHz, every time the machine goes into grinding mode and records the entire dataset from all the sensors for every produced part. The sensor data, along with machine's process data, is gathered from all the test runs before further processing.

2.1.2 The grinding cycle

A 2-stage position controlled grinding cycle is used with pre-defined cutting speed and feedrate

Table 2 List of sensors installed for condition monitoring.

Measured quantity	Sensor	Target subsystem
Strain	Kistler 9238B	Workhead
Acoustic emission	Parker 247 Ultraspan	Workhead tooling
Vibration	PCB triax A45	Workhead tooling
Vibration	SKF CMSS2200	Elec. motor (grinding)
Vibration	SKF CMSS2200	Elec. motor (workhead)
Vibration	IMI601A01	Grinding spindle
Temperature	NTCALUG02A103F	Grinding spindle
Temperature	NTCALUG02A103F	Workhead spindle
Temperature	NTCALUG02A103F	Workhead tooling

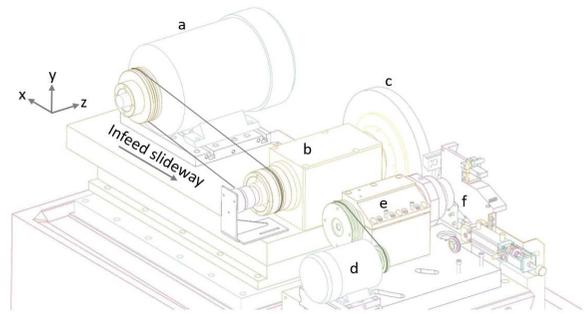


Fig. 3 The schematics for machine and subsystems. a.Grinding Motor, b.Grinding Spindle, c.Grinding Wheel, d.Workhead motor, e.Workhead Spindle and f.Workhead Tooling

[24]. The grinding cycle consisting of 1. *Rough* and 2. *Sparkout* stages is shown in figure 4. A fixed approach known as *air grinding* stage is used where the grinding slide approaches the ring with a higher speed than the grinding feedrate. This stage is programmed with the grinding allowance available to account for the incoming size and position of the ring, until close to contact, in the workhead tooling. Typical grinding force and power measured during the corresponding stages of the programmed grinding cycle are shown in figure 5. The herein described grinding cycle do not use in-process diameter measurement and in order to achieve a fixed output diameter, the machine is preconditioned and the cycle is adjusted to ensure that the desired dimension is produced for the incoming rings. This, despite using a simpler grinding cycle, is to ensure that the production machine setup procedure is followed and the rings are ground to same dimensions as in

production. Therefore, the quality of the produced rings in the experimentation can be measured using company standard measurement equipment.

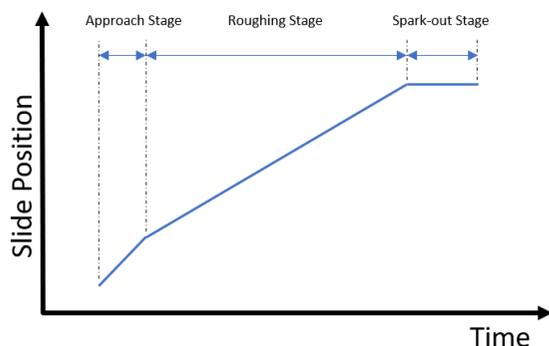


Fig. 4 The programmed grinding cycle.

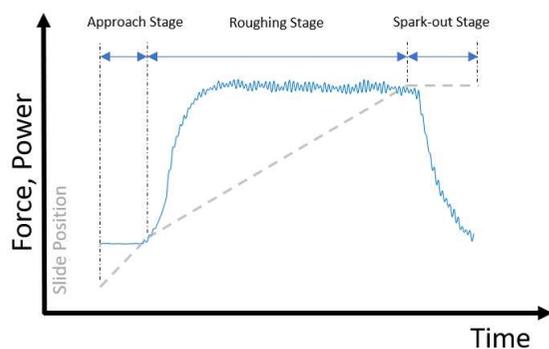


Fig. 5 The typical resultant force and power of the grinding cycle.

2.1.3 Experimental Tests

For this study the machine is prepared to produce parts for the selected cycle type under predefined machine conditions to replicate failures experienced in production. The failure modes are identified from the maintenance history of similar machines in the factory and where the five 5 failures are selected based on the frequency of occurrence and impact on produced quality. Table 3 lists the sequence of experimental test runs for respective failure modes. Baseline tests in the beginning and at the end of the experiment ensure the reference machine operation is achieved against which the failure condition performance is evaluated.

During normal production the incoming unground rings have variations in terms of roundness and grinding allowance which can cause significant variations in the cycle behaviour towards final output quality. Although this is accounted for by using a multi-stage grinding cycle, however, to keep consistency throughout the experimental test runs, the input rings are pre-rough ground to have equal grinding allowance for all the test runs. Figure 6 shows the rings where *a* is the incoming hardened rings also known as *black* rings. After a little bit of stock removal, *pre-rough*, *b*, rings with same diameter are achieved. These rings are used for the tests with remaining grinding allowance of approx. $500\mu\text{m}$ on diameter.

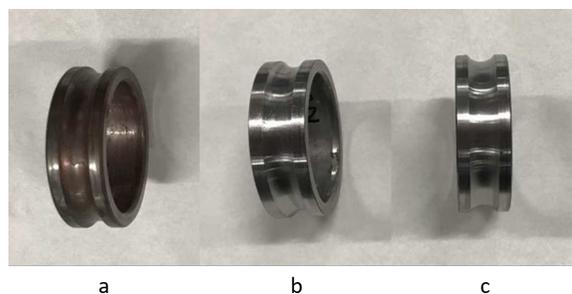


Fig. 6 The workpieces (rings) used in the machine. *a*) Black, *b*) Pre-rough and *c*) Ground ring

It is important to gather enough data to statistically balance out the variations within the tests and have equally distributed data to avoid over representation of any particular test type. Hence, for each test, a dressing interval of 15 rings is used where the grinding wheel is dressed after every 15th grinding cycle. In each failure mode test, a few dressing intervals are used to adjust the grinding cycle to produce rings in desired dimension. This allowed the machine to be properly preconditioned and to reach a level where parts are consistently produced with same amount of material removal. After reaching the steady production, a series of 7 dressing intervals comprising of 105 rings are produced. The total number of rings produced in this experimentation becomes 735 as depicted in figure 7. This procedure is repeated for each failure mode test and set of rings thus produced are labelled for traceability and stored for measurement and future analysis. As described in section 2.1.1 the data is simultaneously acquired

Table 3 List of test cases for selected failure modes.

Id	Test/Failure mode	Failed component	Reason in production
1	Baseline	Reference condition	nominal operating condition
2	Belt Damage	Workhead drive belt	aging or material failure
3	Unbalance	Workhead Spindle	material wear/failure
4	Setup	Drive plate	material wear/failure
5	Setup	Workhead tooling	set up error, material failure
6	Worn out	Workhead tooling support	aging, material failure or crash
7	Baseline	Reference condition	nominal operating condition

for each grinding cycle and for individual ring produced in the machine. MATLAB is used as the main analysis tool for data exploration and processing as well as for the analytical framework development.

2.2 Data processing

As described in the section 2.1.1, the sensors listed in tables 1 and 2 are mounted on the machine and are acquired every grinding cycle of the machine's operation. The dataset is built from the data collected throughout the experimental test runs. Since the data is already saved according to individual rings, there is very little work needed to consolidate the data to start exploration. The data is accessed directly from the network storage and database and imported into MATLAB for exploration and further processing. Sensor data is

sampled continuously at high frequency to include all the process dynamics to ensure high data fidelity of measured quantities. To avoid aliasing, anti-aliasing filter of 43kHz is added before the analogue to digital converter. Although very high frequency of sampled data is not required for sensors other than vibration sensors, it keeps the data acquisition setup simple at cost of added memory required for storage. At the time of data read into MATLAB, an initial filtering is applied to bring the data to desired frequencies that corresponds to machine and process dynamics. This includes low-pass filtering of sensor data and the time landmarks are identified from the process parameter data where the grinding cycle changes from one stage to the next.

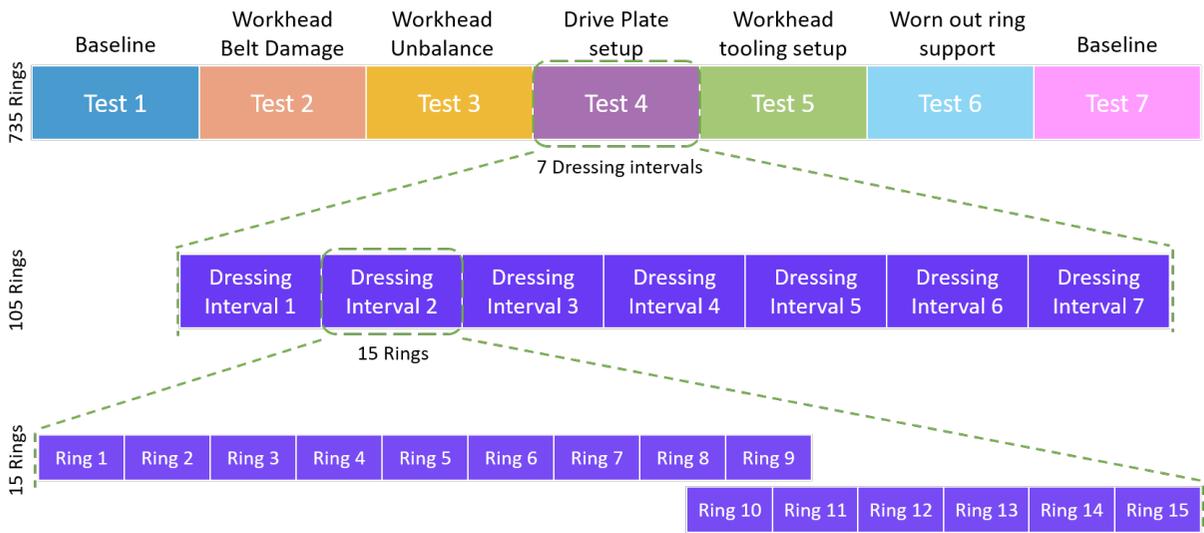


Fig. 7 The experimental test runs where *drive plate* failure mode (*test 4*) is expanded to show the dressing cycles and the rings in each run.

2.2.1 Segmentation

Taking advantage of the knowledge of cycle helps building a better predictive model [18]. Hence the grinding cycle for each ring is segmented into cycle sections based on start of grinding before the grinding wheel makes the contact, force transient where the force in the system start to rise just after the contact before reaching grinding steady state, grinding slide travel during rough grinding and finally sparkout at the end of the grinding cycle. Combining change in gradient in timeseries signal of acoustic emission sensor with the process parameters from machine data, the segments are calculated for individual ground ring. The contact detection in the beginning of the grinding cycle is used to calculate the actual length of grinding cycle using true feedrate and the length that the grinding slide travels to grind the ring. The change of gradient in the signal data help identify the steady state of the grinding forces. Hence, these segments, for the typical force curve in the used grinding cycle, are presented in figure 8. This segmentation divide the time series data from each sensor for individual ring into 4 segments. The change in the cycle of time domain signal from Acoustic Emission sensor is used to identify the segments for each ring. The 3 segments of the cycle which are considered for further processing are listed in table 4. The building forces part of the cycle is omitted due to presence of transients resulting from initial contact of grinding wheel and the ring. From each individual sensor signal segment, time domain as well as frequency domain features are extracted.

Table 4 List of segments corresponding to programmed grinding cycle stages for time domain sensors data of individual cycle.

Segment No.	Name	Grinding cycle Stage
1	Idle segment	Approach Stage
2	Steady Grinding segment	Roughing Stage
3	Spark-out segment	Spark-out Stage

2.3 Feature Extraction

Signal processing using low pass filtering of the sensor signals according to process dynamics as

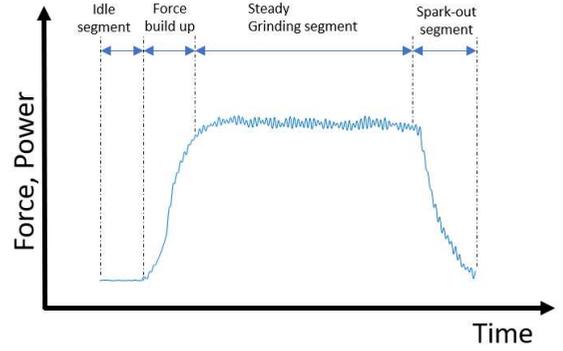


Fig. 8 Segmentation of grinding cycle.

part of data processing step and segmentation plays a crucial role in identifying the parts in the timeseries sensor data from where the features are extracted. It is possible to extract infinite amount of features from the signals. The objective here is to retrieve the maximum information by applying mathematical transformations, either linear or non-linear. By transforming the feature space, the combination of the features can give new information. The statistical features are calculated from sensor signal segments in the time and frequency domain with equations in table 5, for the variable vector x built with N observations.

Table 5 Features in both the time and frequency domain that are calculated for all signal segments

Id	Feature	Equation
1	mean	$\mu = \frac{1}{N} \sum_{i=1}^N x_i$
2	standard deviation	$S = \sqrt{\frac{1}{N-1} \sum_{i=1}^N x_i - \mu ^2}$
3	skewness	$s = \frac{E(x-\mu)^3}{\sigma^3}$
4	kurtosis	$k = \frac{E(x-\mu)^4}{\sigma^4}$
5	root-mean-square	$x_{rms} = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i ^2}$
6	peak-to-peak	$x_{pp} = \max(x) - \min(x)$
7	crest factor	$C = \frac{ x_{peak} }{x_{rms}}$
8	band power	$P = x_{rms}^2$
9	energy	$E = \int_1^N x(i)dN \approx \frac{1}{2} \sum_{i=1}^{N-1} (x_i + x_{i+1})$

In addition to the 9 features in table 5, 90th percentile is also used as a 10th feature to cut-off potential outliers. For the frequency domain features, *FFT* algorithm in Matlab is used to calculate frequency spectrum after removing the low frequency trend from the timeseries data. Although the feature selection is employed at a

later stage, the feature calculation itself can be computation heavy and time consuming. Therefore, the feature list for the scope of this work is chosen based on the relevance to the machine failure classification [25, 26], simplicity and calculation efficiency.

2.4 Sensor(s) and Feature selection

Sensors are needed in accordance with the right failure mode to be detected in the machine. Not only the right type of sensor is important, but also the right location becomes crucial in efficiently and timely detection of the faults in the machine. In this section the methodology developed for sensor ranking and selection criteria based on top features for the failure classification is presented. As discussed in section 2.3, individual grinding cycle segments are used to extract features in time and frequency domain which results in a large feature set. To reduce computational cost of classifier training, the features that are the most representative of the variations in failure mode test classes are to be selected.

A number of feature selection techniques like fisher score [27], chi-squared [28] e.t.c. can be used for the type of classification problem at hand. Also to keep the feature set representative of their physical source, principal component analysis is not considered as dimensional reduction step. Instead MATLAB implementation of neighbourhood component analysis (NCA) [29] is used for feature selection due to its computational efficiency and insensitivity towards irrelevant features in high dimensional feature space. The NCA algorithm in Matlab determines the feature weights by using a diagonal adaptation of NCA with regularization while minimizing an objective function that measures the average leave-one-out classification loss over training data. The feature set is sorted according to weights and top features are selected for sensor ranking.

2.4.1 Sensor Ranking

Based on the feature ranking achieved using NCA, a sensor ranking criteria is defined as depicted in algorithm 1. This results in sensors being weighted based on their features and frequency of occurrence in the top feature list. The sensor ranking is achieved through sorting the weights. Through

incorporation of domain knowledge related to setting up of grinding process in the machines, the sensors are chosen from the ranking list as per the cost and complexity of their installation in the machine and their relevance to the process and failure mode measurement. The dropping of sensors reduces the feature set further to improve the selection of simpler classification models with reduced complexity and better overall performance through increased generalization without having to train on extremely large datasets.

Algorithm 1 Calculating Sensor Rank from list of top features

Input:

S : List of all sensors

F : List of top features

for $i \leftarrow 1$ to length of S **do**

for $j \leftarrow 1$ to length of F **do**

if $F_j \in S_i$ **then**

$R_i \leftarrow R_i + \frac{\text{length of } F-j}{\text{length of } F}$

end if

end for

end for

Output:

R : Rank of sensors

2.5 Classifier(s) Training

In the CBM context, failure diagnostics holds the key to predictive maintenance. Therefore, for efficient implementation, a two step classification framework is proposed with separate classifiers to be trained for failure classification. The first failure classifier, also named as *binary* classifier is to detect the presence of a failure mode in the grinder and the second classifier's, the *multi-class* classifier, aim is to predict the type of the detected failure mode. This classification framework along with the CBM steps leading upto classification is presented in figure 9.

Separate training and test datasets for both classifiers are prepared using stratified sampling to avoid class skewness with 70% – 30% split. $k - Fold$ cross validation with $k = 5$ is considered for this analysis instead of a separate validation set. From the training feature set, it is also made possible to select features from individual or all segments for the training of classifiers. Feature

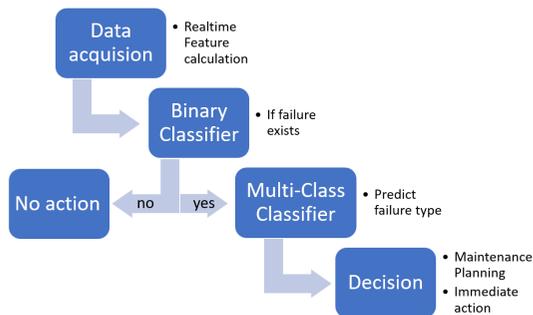


Fig. 9 Failure mode prediction framework

ranking for binary classification is used to select sensors and the corresponding features in training the binary classifier. The training set for the multi-class failure mode classification is adjusted to have the feature list from binary classification. The advantage of using the this two step classification framework is the generalization of the failure classification. Although it is difficult to create every possible failure in the grinding machine to train a perfect classifier, the binary classifier in the presented approach significantly reduces the need to have data from many failure classes. If the features from the incoming data are different from feature set from the baseline tests, the classifier should be able to detect presence of a failure mode. The multi class classifier provides the root cause through supervised training of the classification model.

2.5.1 Model Selection

For failure diagnostics in CBM, supervised learning models like support vector machines (SVM) [20], k-nearest neighbour [30], neural networks [31] and decision trees [9] e.t.c. can be used for classification. However, for the scope of this work the classifiers in the Matlab's classifier app are benchmarked using training dataset for multi-class classifier. Therefore, top performing random forest using the default hyper-parameters as listed in table 6 is selected as the model for both the classifiers. The tuning of these hyper-parameters is not considered in this work.

2.6 Failure diagnostics testing

The test datasets and specifically the multi-class classification dataset is used to verify failure diagnostic framework as depicted in figure 9. The

Table 6 List of default hyper parameters used for training of "Fit ensemble of learners for classification" in MATLAB.

Parameter	Value
Method	Bootstrap aggregation
Number of ensemble learning cycles	30
Weak learners to use in ensemble	Decision tree
Maximum number of decision splits	$n - 1$ where n is number of observations

probability estimate scores for individual classifiers are used to judge the classification results. Evaluation metrics, e.g. confusion matrices, precision, recall and F1-scores are used to evaluate the performance. Using stratified sampling in preparing datasets for training along with the design of experiments ensures the class balance. Hence the performance evaluation metrics being used are less susceptible to false or less truthful indication of performance. The presence of failure mode and the prediction of the cause of failure or the identification of the failure mode is used to support the decision making process in a CBM setup. The maintenance action can be planned or triggered based on the probability score of the classification that gives a level of confidence in failure prediction using the proposed failure mode classification framework.

3 Results and discussion

From data acquisition through CBM setup in the bearing ring grinder and from data processing and feature engineering to training of classification models for failure diagnostics, the results achieved are presented in this section. As described in the section 2.1.1, the machine equipped with sensors for process control is complemented with additional sensors for condition monitoring with the aim to implement the CBM framework for failure diagnostics. Process and sensor data is continuously acquired from the machine for the experimental tests where the failure in the machine subsystems, as per the table 3, are introduced to simulate production level breakdowns and maintenance issues. The raw data is processed in the data processing step to prepare it for feature engineering.

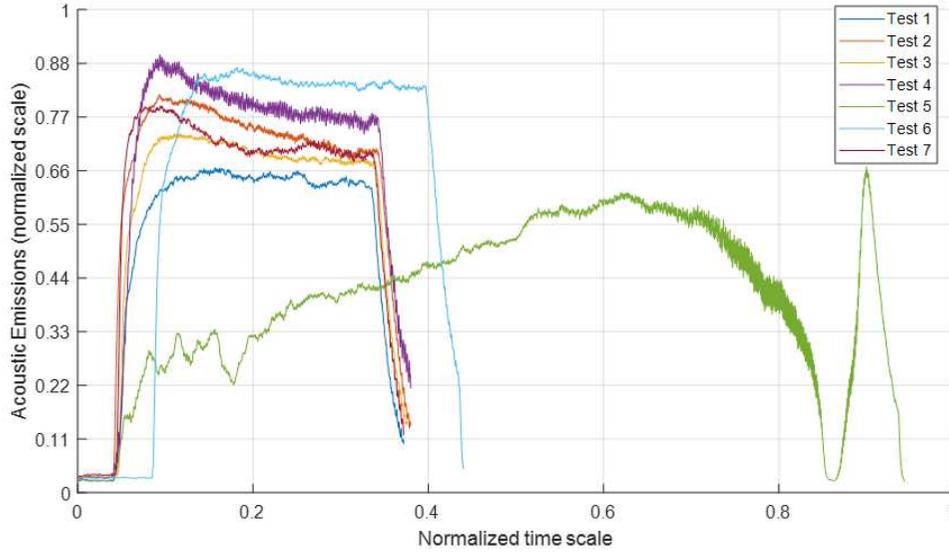


Fig. 10 Acoustic Emissions sensor data from first ring of seventh dressing interval in all the test runs

As mentioned in section 2.2, individual grinding cycle data is acquired for all the sensors. Acoustic Emission sensor data from first ring of seventh dressing interval in every test run is displayed on a re-scaled axes in figure 10.

It is evident that each of the test runs results in different behaviour of the grinding cycle, even the both baseline runs, *test 1* and *test 7*, have some differences. The significant difference, apart from some shift in start of the grinding feed due to dependency on the contact detection, is the total length of cycle in each test. E.g. the cycle for the workhead tooling setup failure mode in *test 5* is around twice as long as other cycles. This is due to the fact that the machine is using a position controlled grinding cycle and it continues to grind until output dimension, in terms of end position, is reached. The wrong setup of the tooling, in this case, affects the ring's position relative to the grinding wheel. Thus the grinding wheel slide has to travel more with the feedrate to reach desired final ring dimension.

The key step of segmenting grinding cycle into parts representing different stages of the process is achieved through combining acoustic emission signal and the process information from the machine controller as described in section 2.2.1. These segments from the the acoustic emission signal in baseline test (*Test 1*), are presented in figure 11. It can be seen that the segment 3 starts slightly

before the change of derivative or the big drop at the end of the rough grinding stage. This the system relaxing in spark-out stage from all the force built up during the grinding process and at this stage the final profile of the ring surface materializes.

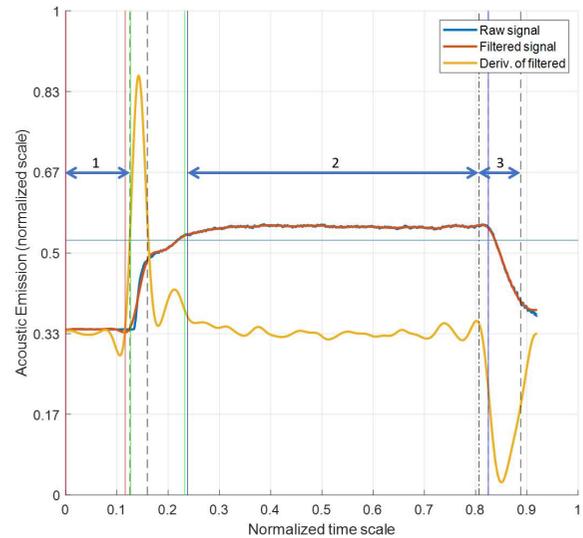


Fig. 11 Processed grinding cycle segments corresponding to table 4. 1.) *Idle Segment*, 2.) *Stead grinding segment* and 3.) *Spark-out segment*.

The feature set, described in section 2.3, is extracted from the three segments from each sensor signal. Representation of the features according to the segments also allows to see the affect of individual part of the cycle in classification performance. Figures 12 and 13 show the feature scatter plots from segment 3 of the grinding cycle.

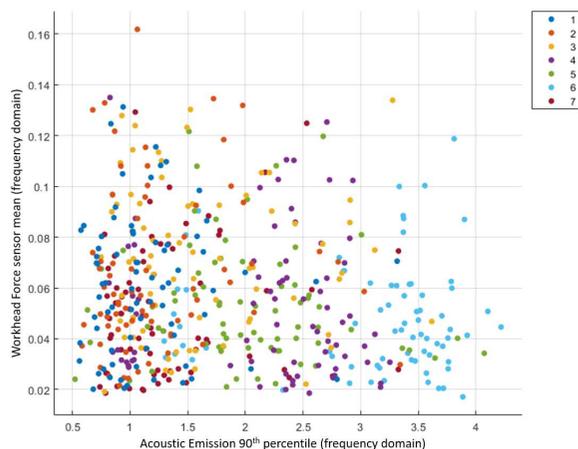


Fig. 12 Scatter plot for selected features extracted from Workhead force sensor on x-axis and Grinding spindle Acoustic Emission sensor on y-axis. The colors show test cases 1 – 7 as listed in table 3

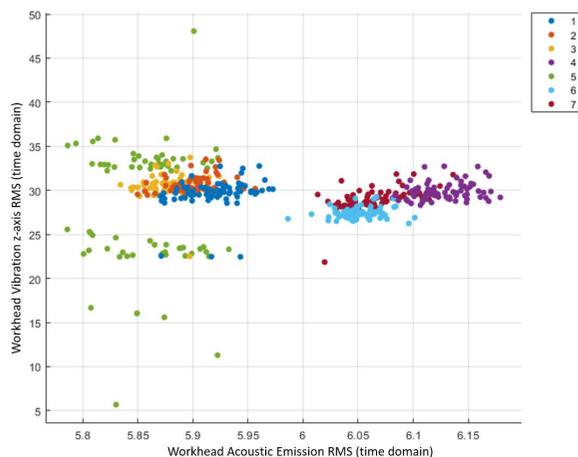


Fig. 13 Scatter plot for selected features extracted from Workhead vibration sensor (Z) on x-axis and Workhead Acoustic Emission sensor on y-axis. The colors show test cases 1 – 7 as listed in table 3

The feature selection, as explained in section 2.4, from the NCA in Matlab is used to identify top features for dimensionality reduction. Since the NCA method uses the label to optimize the feature selection, top feature list will vary based on the grinding cycle segments considered for feature extraction and the class labels used. According to the classification approach proposed in this article, the top features are identified for the binary classification i.e. the features to detect the presence of failure mode in the machine. The feature ranking, from individual segments as well as considering all segments, are presented as the heat maps in figure 14.

It is to be noted that considering individual or all segments together will give different feature ranking list as evident from the heatmap where the top ranking feature value is 250 and the lowest rank feature gets the value 1. In the figure 14, the feature matrix of segment 1, depicted by *a*, it can be seen that few of the features are active specially from the sensors mounted on grinding slide. As soon as the grinding wheel comes into contact with workpiece in segment 2 and 3, figure 14 *b* and *c* respectively, the sensors related to grinding cycle becomes more influential e.g. the electrical power for grinding motor as well as the grinding force sensor. Despite extracting features from individual segments, using all segments for feature selection distributes the feature significance throughout the heatmap as seen in *d* of figure 14. Thus using individual segments allow few number of sensors to be chosen based on their ranking from the top feature list. This, however, does not give a definitive picture of sensor ranking which is required to reduce feature set further.

For the analysis undertaken in this work, top 100 features according to NCA are chosen to determine sensor ranking. As per the proposed sensor ranking criteria, explained in section 2.4.1, the higher the feature in the top feature list, the more ranking is given to the respective sensor and vice versa. Also more features from the same sensor in the top feature list will also result in the sensor getting a higher rank. This gives the sensor ranking as shown in table 7 where the sensor ranking changes based on which segment is used for feature selection for binary classification using NCA method.

This approach of sensor ranking also allows to choose the sensors that further reduces the list of

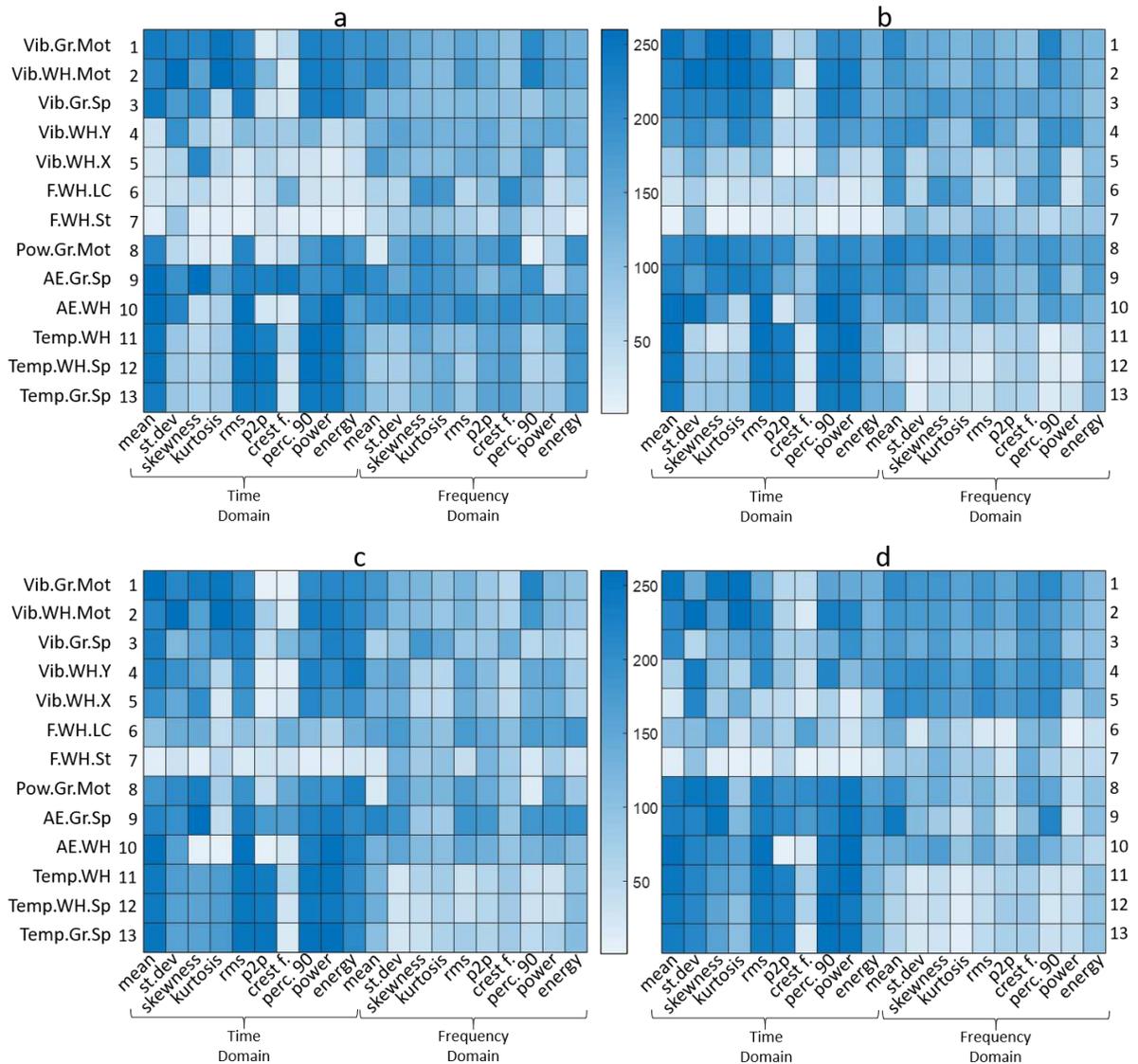


Fig. 14 Heatmap of top features as per the source segments in figure 11. a) segment 1, b) segment 2, c) segment 3 and d) all segments. Higher value indicate higher feature ranking. Here Vib = Vibration, Gr = Grinding, Mot = Motor, WH = Workhead tooling, Sp = Spindle, F = Force, LC = Load Cell, St = Strain gauge, Pow = Electric Power, AE = Acoustic Emission, Temp = Temperature.

selected features. This decision can not only be based on the type of measurements to be included in model training but also based on the ease of installation of sensor(s) and costs associated with it. The choice of selecting segment(s) and the sensors also depends upon the failure modes that are to be detected and classified. As evident from the table 7 for the sensor ranking achieved in binary classification, the sensors moving towards the top of the list for segment 2 and segment 3 are the ones

installed for the purpose of process control. It is to be noted that the sensor ranking from segment 3, where the grinding cycle has reached steady state and the spark-out stage has started, evidently enlists top sensors which give direct measurements related to the grinding cycle performance. During segment 3 of the grinding cycle, the quality of the product is being defined as the grinding slide stops moving and removing further material, thus it can give better clue of the presence of failure mode

Table 7 Sensor ranking based on top 100 features from respective segments. Here Vib = Vibration, Gr = Grinding, Mot = Motor, WH = Workhead tooling, Sp = Spindle, F = Force, LC = Load Cell, St = Strain gauge, Pow = Electric Power, AE = Acoustic Emission, Temp = Temperature.

Segment 1	Segment 2	Segment 3	All segments
AE.WH	Vib.WH.Mot	AE.Gr.Sp	AE.Gr.Sp
AE.Gr.Sp	Vib.WH.Y	Vib.WH.Mot	Vib.WH.Mot
Vib.WH.Mot	AE.WH	Vib.Gr.Mot	Vib.Gr.Mot
Vib.Gr.Mot	Pow.Gr.Mot	Temp.Gr.Sp	Temp.WH
Temp.WH.Sp	Vib.Gr.Mot	Temp.WH	Vib.WH.Y
Temp.WH	Vib.Gr.Sp	Temp.WH.Sp	Temp.Gr.Sp
Temp.Gr.Sp	AE.Gr.Sp	AE.WH	Pow.Gr.Mot
Pow.Gr.Mot	Temp.WH	Vib.WH.Y	Temp.WH.Sp
Vib.Gr.Sp	Temp.WH.Sp	Pow.Gr.Mot	AE.WH
F.WH.LC	Temp.Gr.Sp	Vib.Gr.Sp	Vib.WH.X
Vib.WH.X	F.WH.LC	Vib.WH.X	Vib.Gr.Sp
Vib.WH.Y	Vib.WH.X	F.WH.LC	F.WH.LC
F.WH.st	F.WH.St	F.WH.St	F.WH.St

and its affect on the output quality. Choosing the right sensors in this step boosts the overall performance of failure diagnostics as the same sensors and their corresponding features are used to train both binary and multi-class classification models. Therefore, the failure modes influencing the grinding cycle performance, i.e. affecting the quality of the parts being produced, can be captured by choosing sensors related to process control in addition to conventional condition monitoring sensors.

The selected classification model is the random forest as per the MATLAB's classification learner app benchmark figures presented in the table 8. Here the combined training set is used to learn all 7 classes of the failure mode tests using data from all sensors, cycle segments and their corresponding feature set. Although the performance advantage is not very drastic between random forest and support vector machine models, the random forest model is chosen in this work for its use in similar applications and advantages in multi-class classification in comparison to support vector machines.

In light of condition monitoring as part of CBM implementation, grinding cycle segment 1 is chosen for the failure classification presented in this article. Segment 1, *idle segment*, is where the grinding wheel has not yet come into contact with the workpiece. If the failure mode gets detected

Table 8 Bench-marking of classification models in MATLAB's classification learner app.

Classification Model	Training Accuracy
Random Forest	99.8
Support Vector Machine	96.6
Decision Tree	93.1
KNN	91.4

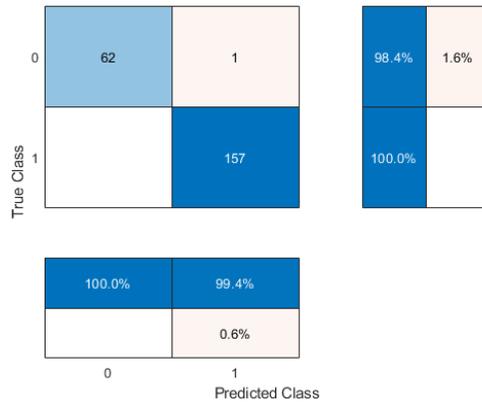
and identified through segment 1, then, the uncertainty of quality deviation due to the presence of failure can be reduced. This will also allow to take action before the scrap gets produced due to affected grinding performance. Table 9 lists the sensors chosen from segment 1 sensor ranking list of table 7. The choice of sensors, as mentioned before, is not just choosing the top ones, rather the decision here is made considering both the failure modes as part of failure diagnostics and the effort, cost of installation of additional sensors and sensor systems in the machine. For example, the reason for not choosing force sensor is the cost associated with the installation is higher than the rest of the sensors. Therefore, through this selection criteria, the sensors considered are listed in table 9.

These sensors correspond to 58 features from both time and frequency domains. Using this feature set, the binary and multi-class failure mode classifiers are trained on their respective training sets with the accuracy of more than 99%. The evaluation metrics are calculated from the unseen

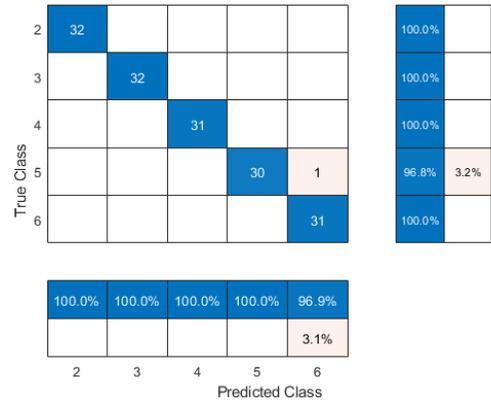
Table 9 Result of sensor selection based on top feature availability and installation cost.

Measured quantity	Sensor	Target subsystem
Acoustic emission	Dittel m6000	Grinding spindle
Acoustic emission	Parker 247 Ultraspan	Workhead tooling
Vibration	SKF CMSS2200	Elec. motor (grinding)
Vibration	SKF CMSS2200	Elec. motor (workhead)
Temperature	NTCALUG02A103F	Workhead tooling

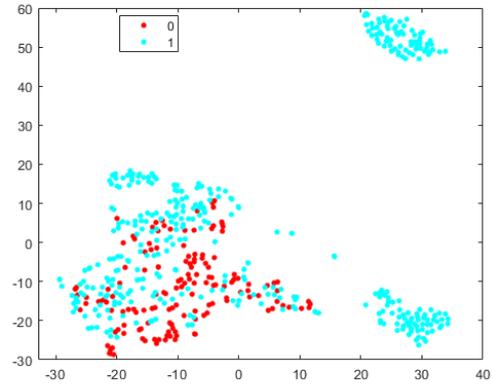
data of test set where the predictions from the trained models are compared to known labels. The resulting confusion matrix for both classifiers are presented in figures 15 and 16.

**Fig. 15** Confusion matrix for binary Random Forest classifier. Here the class 0 corresponds no failure and the class 1 corresponds to failure class.

Using precision and recall from the confusion matrices we can calculate the F1 scores for binary classifier as 99.54% and the global F1-score for failure mode classifier becomes 99.68%. It is evident that the failure mode classifier performs marginally better than the binary classifier. This is due to the potential of clearer separation between individual failure modes in the feature space as some failures affect the machine performance to a larger extent compared to others. On the other hand the binary classification has to struggle a bit to distinguish between no failure and a failure where the machine's performance is not significantly impacted. This behaviour is evident in the

**Fig. 16** Confusion matrix for multi-class Random Forest classifier. The labels 2 – 6 represents the failure modes for respective test types as mentioned in table 3

t-Distributed Stochastic Neighbor Embedding (t-SNE) plots of training set for binary classifier in figure 17 and the failure mode classifier in figure 18. Despite the complexity, the trained classifiers predict with high accuracy as depicted by the evaluation metrics.

**Fig. 17** t-SNE plot for the training data set for binary classifier. Here the class 0 corresponds no failure and the class 1 corresponds to failure class. The complexity and overlap of failure modes are evident that affect the performance of the binary classifier.

This becomes even more significant if the sensor chosen for feature reduction belongs to either process control (Acoustic emission and Force sensor) or condition monitoring (Vibration sensor on the workhead electric motor) only. In case of using process control sensors i.e. acoustic emission and force sensor only, the binary classification

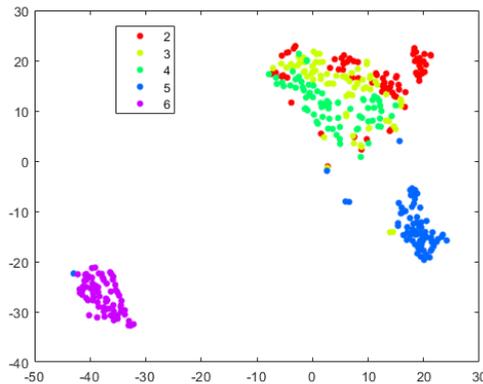


Fig. 18 t-SNE plot for the training data set for multi-class classifier. The class separation of the failure mode tests 2 – 6, from table 3, is visible

accuracy drops slightly to 98.6% however, the failure mode classification accuracy ends up at 90%. This difficulty in failure mode classification shows the overlapping of failure mode classes in feature space. On the flip side if only condition monitoring sensors, i.e. vibration sensors on workhead assembly and motor are used, the binary classification accuracy remains similar at 99.3% and only the failure mode classification accuracy is reduced to 96.9%. The most miss classified failure mode in this case is *Test 4* which is related to *Drive plate* setup. Due to lower intensity of this failure mode, the inclusion of acoustic emission sensor picks up the failure as it affects the grinding cycle performance significantly. This evidently shows strength of choosing sensors which can improve failure diagnostic performance and a trade-off can be made to detect presence of failure only where the additional sensors can result in higher costs.

The resulting classification prediction framework as presented in section 2.5 and depicted in figure 9 is generalized over detecting a failure mode and only then to classify and diagnose the failure mode. This distinction in the classification can be used to trigger maintenance action as part of condition based maintenance strategy. This 2-stage classification framework allows higher performance in training as well as in prediction. The inference pipeline also becomes simpler and the trade-off between two types of classification at the cost of the number of features required can easily be learnt through iterations or separating

feature selection. Using segmentation significantly reduces the feature set and improves model generalization to avoid overfitting. Choice of features based on sensors and grinding cycle segment can be made based on the type failure to be identified. Failure modes related to grinding cycle performance take advantage of segments related to grinding and the CBM failure diagnostics can be achieved even before the start of grinding cycle as presented in this work.

4 Conclusion

This paper presents failure diagnostic framework for the implementation of condition based maintenance (CBM) in a bearing ring grinder. Taking advantage of the complete grinding cycle and using sensors installed for process control as well as condition monitoring results in high performance in failure mode prediction. Data acquired from vibration, acoustic emissions, force, power and temperature sensors, as part of CBM implementation, has enabled generation of high quality labeled dataset used in this work. Failures from machine's maintenance history are adopted for the experimentation and the test runs are designed to achieve a balanced dataset for analysis. Segmentation of the grinding cycle data has enabled to extract features that capture the variations in different parts of the process. Using combination of proposed feature selection and sensor ranking method results in a reduced feature set. The sensor selection criteria allows the features to be filtered based on corresponding sensor importance for the failure mode classification as well as the cost associated with it. The two step classification improves the generalization of failure diagnostics. Model identifying presence of failure as binary classifier gets precedence in establishing the sensors and the corresponding features to be used in failure diagnostics. Combining the use of process control and condition monitoring sensors provide a comprehensive feature set that outperforms in failure classification than the features from independent sensors. Large separation in feature space for failure modes results in marginally better performing multi-class failure classifier using feature list selected for binary classifier. For both binary and multi-class classification models, the benchmarked random forest in Matlab performs with accuracy of more than 99% on test datasets. According to

the proposed classification framework using the feature set from idle grinding segment, the failure mode identification is only triggered if the presence of failure is detected in the data. Adapting advanced machine learning models through use of feature set from multiple cycle segments can enhance the capability of root cause analysis and failure predictability in context of CBM in the bearing ring grinder.

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5.2 Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

5.3 Author Contributions

All authors contributed to the study conception and design. Instrumentation, software, testing, formal analysis, data curation was performed by Muhammad Ahmer. Data collection and analysis was supervised and reviewed by Fredrik Sandin, Pär Marklund and Martin Gustafsson. The first draft of the manuscript was written by Muhammad Ahmer and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.