Efficacy of Statistical Formulations on Acoustic Emission Signals for Tool Wear Predictions

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Abstract: Acoustic emission (AE) signals obtained during machining processes can be used to detect, locate and assess flaws in structures made of metal, concrete or composites. This paper aims to characterize AE signals using derived parameters from raw signatures along with statistical feature extractions to correlate with tool wear readings. Missing tool wear values are imputed using domain knowledge rules and compared to AE signals using machine learning models. The amount of effect on tool wear is formulated using Bayesian Inferences on derived parameters such as areas under the raw signal curve in addition to comparisons with the supervised models for predictions. Using the constructed models and formulation, the presented study also includes a trace-back pseudo-algorithm for determining the stage in process where tool wear values begin to approach the wear limits.

1 INTRODUCTION

A material under stress releases elastic waves from localized deformation sources such as cracks, dislocations, etc. which are termed as Acoustic Emissions. Sources generating AE in different materials are unique. For examples, in metals, primary macroscopic sources are crack jumps, processes related to plastic deformation development and fracturing and de-bonding of inclusions. Quantitative and qualitative characteristics of acoustic emission waves, generated by sources of different nature depend directly on material properties and environmental factors (Grosse and Ohtsu, 2008). Hence, with advanced technologies available to capture and process AE signals in modern applications, the use of AE in detection and analysis of flaws, cracks, corrosion and abnormal conditions in metals has advanced steadily along the lines of statistical analysis, machine learning and data understanding (Al-Jumaili et al., 2016).

Conventional methods like statistical and wavelet analyses are still available and in some cases, the preferred modes of analyzing AE signatures which is evident in (Singh et al., 2012) where piezoelectric sensors were used to identify micro and macro-cracks and their temporal advancement in snow to detect avalanches. In general, with the objectives set in detecting sources of flaws in metals during processes, the application of feature extractions in AE signals is an area of research that are conducted based on the kind of problem at hand, for example, detection of leaks, friction, knocks, chemical reactions, changes of size of magnetic domains, apart from deformation and fracture development in structures. Hence, the development of AE technologies relies on understanding the physical nature of acoustic emission in different materials. To achieve this goal, determination of the interconnections between characteristics of acoustic emission and sources that generated it, is of utmost importance. However, establishing such relations for different materials and structures is a real scientific and technological challenge. The tasks of reaching the correct machining conditions, constructing instrumentation and setups (Chiementin et al., 2010), building data acquisition modules along with predictive networks (Suwansin and Phasukkit, 2021) undeniably contribute variations to AE readings along with the intended capture of the source emissions. From a data mining point of view, a primary problem of analysing AE signals is to be able to derive sustainable parameters from the raw data for comparisons with targets such as crack depths or tool wear amounts or machining temperatures. Since material cutting and deformations effect a certain change in the tools used, a variety of studies focus on establishing links between material changes using AE sensors and damages or

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wears incurred by the tools (Bhuiyan et al., 2016).

This study aims to develop models between multiple features from the AE signals such as areas under curves of the signal, categorical features fed into the process and progressive tool wear observed during the runs. Sections 2 and 3 present the associated works and the developed scheme for comparing AE data with tool wear values. Sections 4 and 5 discuss the results observed from the models with possible integration scenario in industrial applications and concluding remarks.

2 ASSOCIATED LITERATURE

Notable literature using acoustic emissions in their study present mainly two kinds of analysis: conventional studies using signal analysis and machine learning techniques. The conventional methods comprise of extracting statistical data indicators such as Root-Mean-Square values, kurtosis, signal envelope, etc. Early studies using statistical relations based on AE comprised of detecting correlations between AE and physical characteristics of materials such as (Carpenter and Zhu, 1991), (Pearson et al., 2017), where correlations were observed between AE signals and fracture toughness of cast iron under compression tests. In (Usgame et al., 2013), the authors present a comparison of time based fault indicators such as peak value, RMS, ring-down counts and kurtosis to detect faults in tapered roller bearings. In recent decades, structural health monitoring (SHM) has become an inclusive concept of developing methods for prognostic and diagnostic monitoring of engineering builds based on materials (Khan, 2018), for example inspections of bolted joints (Du et al., 2018), metal pressure vessels, pipes, concrete bridges, rotating machinery, cutting tools, etc. with the help of material studies. Some specialized statistical approaches are also developed in the context of obtaining significance of signal unbalances in machine equipment. This was used in (Niknam et al., 2013) where a Zero-Inflated Poisson (ZIP) regression model was developed to handle over-dispersion and zeros of the counting data from bearings along with Generalized Linear Models (GLM) which were used to perform categorical data analysis.

With modern data based learning techniques such as machine learning (ML) and deep learning (DL), the studies involving AE data has expanded to include localization and fault detection problems using AE signatures on a large scale. In (Suwansin and Phasukkit, 2021), the authors constructed a specialized neural network with a majorization-minimization cost function optimization to predict cracks in welding joints of steel rail under a load using a single AE sensor. The results from the study were also compared with actual results obtained directly from Phased Array Ultrasonic Testing (PAUT) and they showed that the accuracy scores of the proposed AE based scheme reached 77.33%. Image based deep learning was implemented in (Mokhtari et al., 2020) on AE image data to localize crack sources and defects. The computational expenses were also huge as compared to traditional studies. An array of AE sensors with SVM techniques have also been used for analysis in (del Val et al., 2020).

In (Bhuiyan et al., 2016), the progressive tool wear in turning process was studied using continuous monitoring of the amplitudes of AE signals obtained from piezoelectric sensors placed on the tool holder. The continuous type signals were observed for different feed rates and depth of cuts factors to distinguish between observed signals with inherent noise from tool holder setup along with chip formation and the pure signals from only tool wear. The study determined that the amplitude of AE signal increased with the increase of tool wear and depth of cut i.e. with the increased rate of material removal.

Even though each AE signal is a time series, the complex dependency of tool wear on the different phases of AE cannot be generalized using conventional time series methods. Therefore, this study proposes a work-in-progress prediction scheme that is statistical model based, specifically Bayesian formula based along with classification and regression algorithms to provide a complete monitoring process devoid of dominant signal analysis. Temporal dependencies are not considered, and with simple derived parameters from the given pre-processed AE signals, the authors here present a multi-modeling approach on different cases of AE signals from the same milling process based on different conditions. Classifications to detect parameters fed before the process and regressions to predict tool wear values for a given AE signals are implemented. The Bayesian model is used to determine the pattern of tool wear degradation based on derived parameters from the signals. These early investigations are carried out on a single public dataset to verify whether the models yield reasonable inferences.

3 DATA MINING APPROACH

We begin this section with a description of the considered data followed by parameters deriving approaches. Further, machine learning models are built to assess the relationship between the different features.

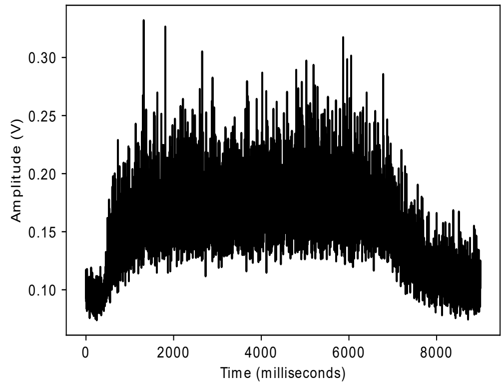


Figure 1: An Acoustic Emission Signal from Sensor mounted on the Worktable.

3.1 Acoustic Dataset Description

The data used in this study is a collection of experiments from runs on a milling machine under various operating conditions (Agogino and Goebel, 2007). In particular, tool wear was investigated in a regular cut as well as entry cut and exit cut. Data was sampled by three different types of sensors (acoustic emission sensor, vibration sensor, current sensor) and acquired at several positions. This paper utilizes only the acoustic raw signatures captured from the acoustic sensor model WD-925 (Physical Acoustic Group, frequency range up to 2MHz) mounted on the table of a Matsuura machining center MC-510V in the experimental set-up. The signals captured are amplified, filtered and fed through two RMS devices before they enter the computer for data acquisition. The proposed analysis can also be conducted on the data from the other AE sensor attached to the spindle and hence, it is excluded from the study presented here. The points are provided in raw format as amplitude in volts against time in milliseconds. A typical AE signature from the milling process where the sensor was placed on the table next to the tool insert shaft is shown in Figure 1. The collective data presents 16 cases with varying number of runs that was dependent on the degree of flank wear on the used tool measured between runs at irregular intervals up to a wear limit (and sometimes beyond). The readings were not always measured and at times when no measurements were taken, no entry was made, presenting missing values in the data. Hence, imputing rules are defined in later sections. The imputation is done using self-constructed rules, knowing the behavior of the processes involved. A brief distribution of these 16 cases is presented in Table 1b with different parameters of processes such as Depth of Cut (DOC), Feed and Material. These factors form the external categorical features used in training data. The tool wear recorded in this process is the flank wear that occurs due to friction of the tool on the work-piece.

The columns corresponding to an AE signature in every case are *run, Flank Wear, time, DOC, feed*, and *material*. We denote the variable Flank Wear in this study with TW, denoting Tool Wear. Each captured raw signature corresponds to one of the runs (somewhere in time), while it is noted that the captured signals are not uniformly recorded in time domain. So the runs only tell the sequence of the consecutive AE signals. The whole dataset of AE signals comprise of 165 observed samples over all the 16 cases and 2 experiments with 9000 points for every AE signal. Further description of the complete setup and experimentation is provided in the *read-me* section given along with the dataset.

Table 1: Data Description.

(a) Distribution of Cases across Materials and Experiments.

	Experiment 1	Experiment 2
Material 1: Cast Iron	1,2,3,4	9,10,11,12
Material 2: Steel	5,6,7,8	13,14,15,16

(b) Distribution of Parameters across the Cases

Color	Depth of Cut (DOC)	Feed
Red	1.5	0.5
Purple	1.5	0.25
Blue	0.75	0.5
Orange	0.75	0.25

The selection of this data set is made on the basis of availability of pre-processed AE signals for early implementations, before validating this scheme and using it on large scale industrial data-sets. Another factor is the kind of unstructured data collected with missing tool wear readings, presenting an opportunity to apply a customized imputation scheme.

3.2 Usable and Derived Features from the AE Data

A set of features that contribute to AE readings, apart from the source generation and noise inheritance along the transmission, are feeds, conditions and parameters that are set prior to the machining operation. These factors are passive moderators to the variation of emissions, in the sense that they are not actively affecting tool wear as in the case of machine temperatures and sheer stress during the process.

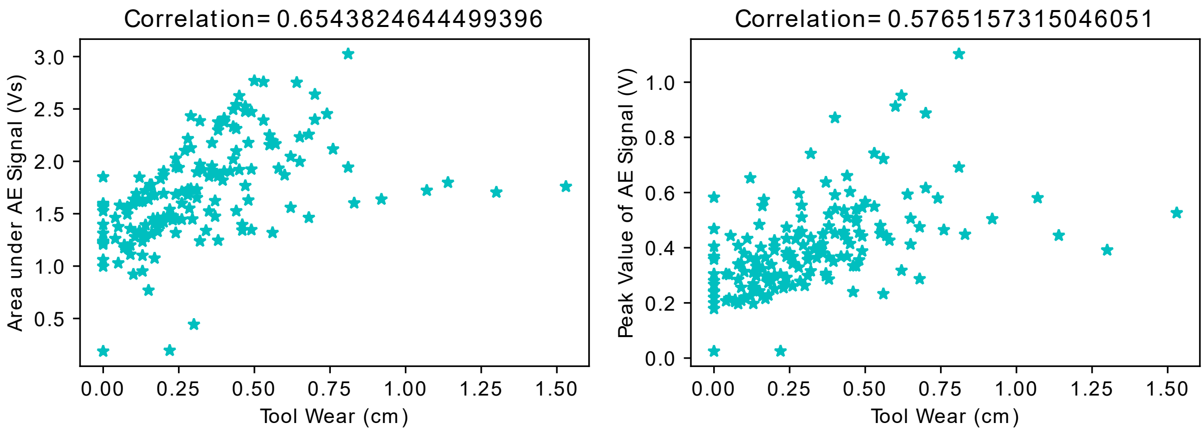


Figure 2: Distribution of Points with Correlation Values.

In addition to the available external features, to develop links between AE data and tool wear, we extract single dimensional parameters from the signal to compare with the target variable. The area under the curve is extracted to correlate with tool wear using trapezoidal rule for integration. Another important parameter for consideration is the peak amplitude of the processed signal. Spearman's correlation coefficient is calculated between the variables and is presented in Figure 2. The values show that area is highly correlated with the tool wear readings than the peak values. Hence, we use the calculated areas in the statistical model formulated in following sections.

3.2.1 Label Imputation Rules

Considering that every recorded AE signature may not be accompanied with a tool wear reading, there is a need to consider these samples in the training of algorithms sensibly. To do it conventionally, a user may be forced to either exclude these readings altogether or fill up the labels with either zero or the average of the readings. Instead in this case, we use the given pattern of collected tool wear readings in a case to fill in the missing values. For every run, the missing value is filled by comparing with its previous or next value.

The following algorithm was used to impute null or missing tool wear readings $TW(i)$ for an index i in the data within the same case:

1. If $TW(i) == Null$ with $TW(i-1)! = Null$ and $TW(i+1)! = Null$, then $TW(i) = avg(TW(i-1), TW(i+1))$
2. If $TW(i+1) == Null$, then $TW(i) = TW(i-1)$
3. If $TW(i-1) == Null$, then $TW(i) = TW(i+1)/2$
4. If $i == 0$, then $TW(i) = 0$

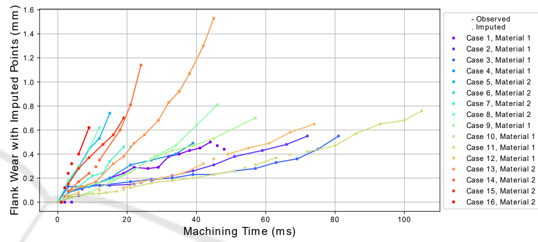


Figure 3: Tool Wear Imputation using the Defined Rules.

5. If i is last index, then $TW(i) = TW(i-1)$
6. The above cases will eliminate $TW(i-1) == TW(i) == TW(i+1) == Null$

Simplistically, a tool wear reading in sequence lies between its previous and next values. For this study, a missing tool wear value is filled by the average of its previous and the next tool wear values. It assumes its previous value if its next value is missing or half of the next value if the previous value is missing. With sequential application in each case, the algorithm will eliminate those cases where both the next as well as previous values are missing. The imputed tool wear readings are shown in Figure 3.

3.3 Predictive Models

Considering the imputed tool wear readings as target, the entire AE data is trained with four regressors, namely Ordinary Least Squares, i.e. Linear, Lasso, Elastic Net and LassoLars. The choice of using the complete data is made to enable the use of scalable Big Data based algorithms when the emissions are captured with a higher frequency rate and at more intervals. Each of the regressors was trained with a cross validation split of 70%-30%, apart from the unknown test set. The regression values determine the approximate amount of tool wear for that captured AE signal. Mean absolute error and mean squared error are the metrics used to validate the models on the test set.

Along with regression models, a supervised learning to yield classifications of the AE signatures is also constructed. The predictions of tool wear readings were done on case to case basis, since each case has its own parametric features that affected the milling process. Without considering the temporal effects on the runs of each case, the attempt to learn the preset external factors selected before the milling process is made to identify relationships between the captured AE signals and the concerned factor. The three factors considered for individual classification are *DOC*, *Feed* and *Material*. The classification models are trained on the entire raw signature data set with the samples shuffled indiscriminately to learn the patterns locally. The data is re-scaled before training using a kernel transformation based on the means of each case. The kernel product reduces the number of columns to 16, one corresponding to each case. The classifiers range from linear models such as logistic regression to tree-based algorithms such as decision tree and random forest. The linear and quadratic discriminant analysis algorithms are used as well. Cross-validation with a split of 70%-30% train-test data is used to reduce overfitting in the models, as in the case of the regression models, with a separate set of the unknown test data. At this stage of investigation, the authors have presented only the necessary models to establish that such links can be extracted between AE data and the target classes, even though the target classes have no direct effect on the emissions acquired from the processes, instead, they affect the milling process whose signals are captured by the AE sensors. Metrics used on the unknown test set are the Accuracy Score and the F1-Weighted Score.

3.4 Bayesian Model for Building AE Relation on Amount of Tool Wear

In this section, we formulate the problem of distributing area covered under the AE signal to the amount of tool wear recorded for that stage in time. The collected AE readings form the exhaustive set of events for the experiment of a machining process. For every case, we calculate the probabilities of having the same acoustic signal along with events where the tool wear for that signal has crossed a pre-defined threshold t. We calculate the probability of a reading for an AE event as follows:

$$P(A_i) = \frac{Area(i)/TW(i)}{\sum_k Area(k)/TW(k)}$$

If E is the event where TW crosses threshold t then

$$P(E) = \sum_i P(E/A_i)P(A_i) \tag{1}$$

The conditional probability that a tool wear reading crosses t after an AE event is captured is given by

$$P(E/A_i) = \begin{cases} P(A_i) \text{ if } TW(i) \geq t \\ 0 \text{ if } TW(i) < t \end{cases} \tag{2}$$

The traceback probability for knowing which AE event begins to start exceeding t using Bayes Probability is given by

$$P(A_i/E) = \frac{P(A_i \cap E)}{P(E)} = \frac{P(E/A_i)P(A_i)}{P(E)} \tag{3}$$

Substituting Eq. 1 and Eq. 2 in Eq. 3, we get

$$P(A_i/E) = \frac{P(A_i)^2}{\sum_k P(A_k)^2}$$

For every predicted tool wear reading from the regression models, the above probability retraces the readings at which an AE event crosses t. Where the events do not cross the threshold, the probability remains zero. Adding subsequent events to the model traces the amount of tool wear degradation once t is exceeded.

The primary assumption for this approach is that the collected AE signals are the only events possible in this process, which may not be maintainable in reality. However, more recorded samples may provide a better AE event prediction for a threshold crossing scenario.

4 RESULTS AND DISCUSSIONS

Figure 4a. presents the metrics of classification models computed on the respective test sets. The highest accuracy scores and F1 scores are obtained in the cases of linear and quadrant discriminant analyses across all the target classes. The tree-based algorithms perform almost the same for the same class with the logistic regression obtaining the least scores in both metrics for all classes. The average best score on the test sets across both metrics from the best performing Quadratic Discriminant Analysis model for classes DOC, Feed and Material are 87.54%, 100% and 85.33% respectively.

Figure 4b. presents the regression model performances. The AE samples having the same set of Material, DOC and Feed present a comprehensive dataset

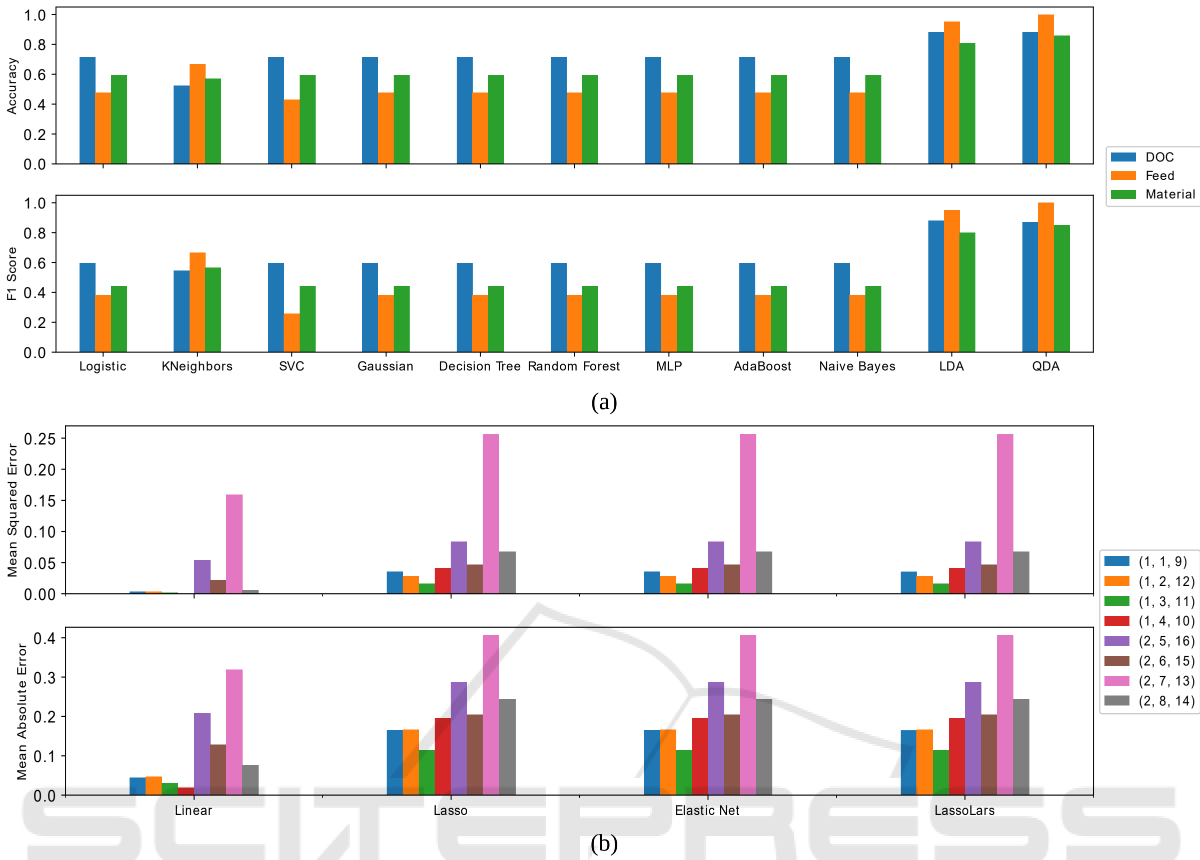
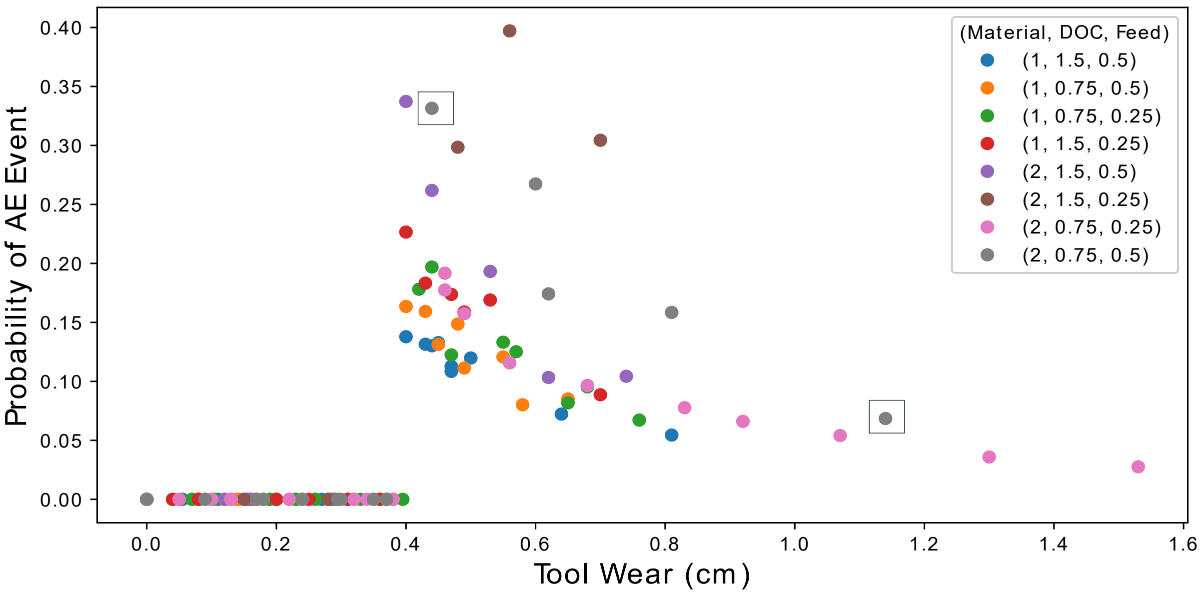


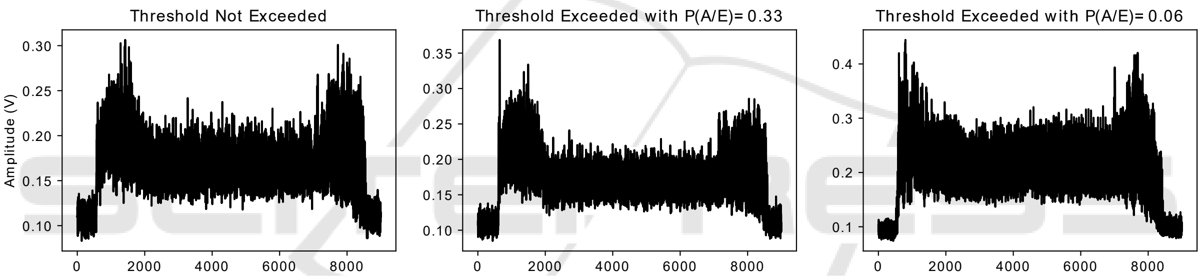
Figure 4: Model Performances (a) Classification Models: AE vs DOC, Feed, Material (b) Regression Models: AE vs Tool Wear.

to be able to predict tool wear under the same conditions. As shown, the linear models show the lowest mean absolute errors and mean squared errors across all the datasets. This can be perhaps due to lower number of recorded samples from the individual cases across the two experiments. The average mean absolute error on the test sets for linear models across the cases is 0.1090 while the average mean squared error is 0.03132.

In Figure 5a., the distribution of events before and after the set threshold $t = 0.4$ is exceeded can be seen. The zero probabilities simply say that the corresponding AE signal has not contributed to the threshold crossing. The decreasing non-zero probabilities indicate those events in which the tool wear has been affected enough to cross the threshold. Higher probabilities indicate greater tendency of deviating AE samples that lead to a higher amount of tool wear, while the lower non-zero values can be interpreted as least contributing towards further tool degradation, however this may change once more samples are obtained and the tool wear amount increases for latter samples. Once predicted tool wear values are obtained, these can be included in the proposed distribution model to visualize the possible degradations over the next set of AE values if available. Temporal dependencies are not used in this approach, which makes it a simpler model to visualize next set of tool wear degradation towards a wear limit beyond the set threshold. In Figure 5a., two AE events are highlighted (boxed) from the data-set corresponding to cast iron material with a DOC value of 0.75 and Feed value of 0.5. The corresponding AE signals are shown in Figure 5b. where the signal exceeding the threshold value 0.4 with a higher probability (center signal) is different from the immediate previous signal where the threshold was not exceeded (left signal). The AE signal where threshold was crossed but has a least probability slightly differs from the remaining two signals indicating lesser impact on tool wear post the event where the threshold was actually exceeded with a higher probability. The combinations of imputed targets and predicted target are valuable to this model since the probabilities are calculated over all the available samples. With lesser samples, this model could lead to skewed values. For validation



(a)



(b)

Figure 5: Comparisons of AE Events with Actual Signals (a) Progression of Tool Wear with every AE Event (b) AE Events from Cases 8 and 14.

of such models, manual comparison with tools at that stage where higher probabilities are predicted, is required, which has not been possible in this case due to the use of public data-set.

Figure 6. presents the outline of integration of proposed statistical and prediction schemes in actual industrial cases. Prediction softwares available commercially can be used in addition to DAQ systems where AE events are captured to simultaneous provide prognostic analysis when the machine is in process. The use of modern embedded controllers such as those provided by National Instruments (NI) can be used to integrate this scheme in industrial scenarios.

5 CONCLUSIONS

Based on acoustic emissions, a mixed analysis using a statistical model and predictive models has been proposed in this paper. The use of machine learning algorithms presents a non-conventional approach to establish relations between emission samples from sensors to observed tool wear. In cases where the tool wear values were missing, an imputation scheme is presented based on the behavior of tool wear. The Bayesian model based on the calculated areas under AE signals and tool wear values give a certain insight into the pattern of approaching a threshold value for manual inspection. Along with predicted tool wear values, this scheme can be used to highlight the process at a certain signal where higher probabilities indicate the effect on tool wear has been significant, while lower probabilities are still open to interpretation. Based on these preliminary investigations, one cannot claim to definitively stop the process where tool is predicted to be highly impacted, but the methods can be validated and implemented on different data-sets for variability. The current scheme may be useful in prognostic cases where small samples of AE data are extracted and used for analysis. However,

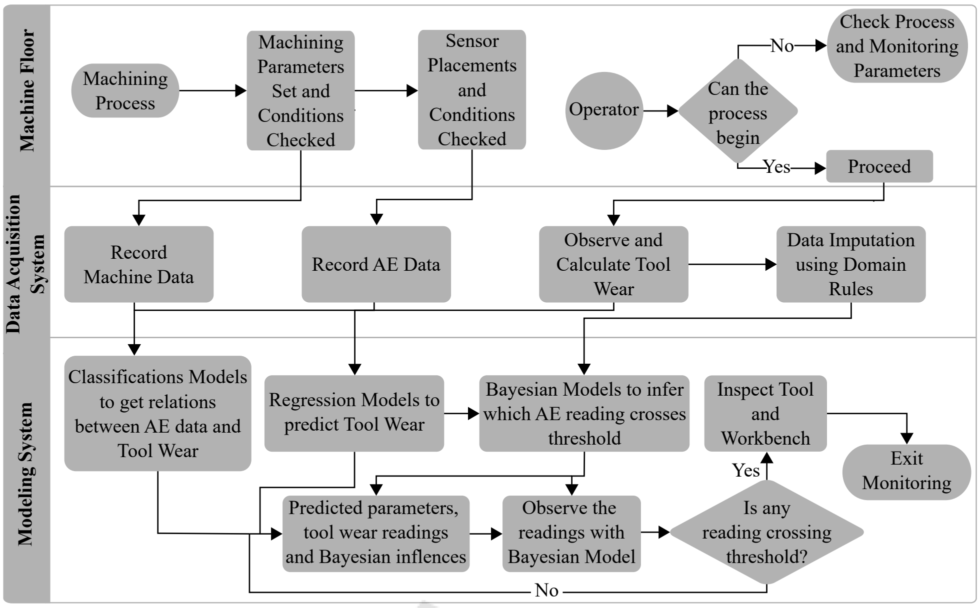


Figure 6: Integration of Prediction Models for Traceability.

with the proposed integration scheme using available DAQ systems, analysis toolboxes and cloud based data distribution, scalable implementations with big data may also be possible. The predictive models can also be compared with advanced neural network analysis along with variation in considered classes from binary to multi-label problems. These directions are planned in future works.

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