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Computer Numerical Control CNC Machine Health Prediction using Multi-domain Feature Extraction and Deep Neural Network Regression

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Abstract: **Tool wear monitoring has become more vital in intelligent production to enhance Computer Numerical Control CNC machine health state. Multidomain features may effectively define tool wear status and help tool wear prediction. Prognostics and health management (PHM) plays a vital role in condition-based maintenance (CBM) to prevent rather than detect malfunctions in machinery. This has great advantage of saving costs of fault repair including human effort, financial costs as long as power and energy consumption. The huge evolution of Industrial Internet of Things (IIOT) and industrial big data analytics has made Deep Learning a growing field of research. The PHM society has held many competitions including PHM10 concerning CNC milling machine cutters data for tool wear prediction The purpose of this paper is to predict tool wear of CNC cutters. We adopted a multi-domain feature extraction method for health statement of the cutters. and a deep neural network DNN method for tool wear prediction.**

Keywords— **Tool Wear Monitoring; CNC machine; Prognostics and Health Management; Condition Based Maintenance; DNN.**

1. INTRODUCTION

The PHM society has held many competitions that are categorized into three types according to their objective; health assessment, fault classification and Remaining Useful Life (RUL) prediction. One of these competitions PHM10 was concerned by the computer numerical control (CNC) milling machine data. The cutting process involves varying and not constant stresses on the flutes of the cutter as they come into contact with the piece, generating wear. Wear is a complicated process that varies depending on the ***setup***, cutter type, and work piece material. As the process progresses, more effort or power is necessary to produce the same amount of cut. The tool wear of the cutter is considered a health index for the CNC machine because as the tool wear increases, the RUL of the machine decreases thus must be scheduled for maintenance. The sound created by the cutting process gets more noticeable as the flute wears. As wear increases result in a loss of surface quality in the finished product and raise manufacturing expenses [1].

To minimize cutting process interruptions, researchers often collect cutting force, vibration, acoustic emission, spindle motor current and power, and other information for online tool wear monitoring. According to studies, time domain, frequency domain, and time-frequency domain characteristics may accurately evaluate tool wear status. For tool condition monitoring, 41 generalized fractal dimensional characteristics of acoustic emission signal, 4 energy features based on empirical mode decomposition, and 18 energy features based on Hilbert transform of cutting acoustic signal were employed in [2]. In [3], they constructed a health index for tool life monitoring using time-frequency domain features of all force, vibration and acoustic emission sensors extracted by wavelet packet decomposition. Multi-domain features of force and vibration signals only were used in [4] for virtual tool wear sensing.

Another research [5] extracted multi-domain features for force and vibration sensors for tool wear prediction using a deep learning model. However, Acoustic emission (AE) is transient elastic energy released in materials undergoing deformation so it we will be taken into consideration in our study. Prognostics is condition-based health assessment that includes detection of failure indicators from sensory data, prediction of RUL by generating a current state estimate. The meaning of "prognostic" is "anything that predicts. A prognostic concern in the PHM community is the assessment of the Remaining Useful Life (RUL) of a component/system or unit. RUL is the amount of time the examined part/machine has until it fails [6]. Prognostics techniques is classified as: physics-based, data-driven. Tool wear prediction is also a prognostic problem that helps RUL estimation for the machine.

Data-driven approaches necessitate historical data about system operation throughout its entire life cycle, from inception to failure, with little/no knowledge of system physics. These approaches have gained popularity in the PHM community because of their ease of implementation and ready-made tools, which are mostly based on Artificial Intelligence AI methodologies. Classical AI includes Random Forest RF, Support Vector Machine SVM and artificial neural network ANN. Many studied adopted these methods for tool wear prediction hence RUL prediction of cutters.

In [7], the authors presented a method for prediction of tool wear in milling operations using Random Forest RF. Then they made a comparative study against earlier ML algorithms in [8]. The authors held a performance comparison between RFs against feed-forward back propagation (FFBP). The study led to the outperformance of RF over other earlier methods. When the size of the data grows, ANN is better used. ANN was used in [9] for the prediction process. Other studies used SVM for the decision-making process in tool condition monitoring [10]. Prognostics is considered a prediction-target problem means a regression task in the world of AI. The evolution of sensors, IIOT and Big data has led to the invasion of deep learning-based models into the PHM. DL architectures including convolutional network, Long Short-Term Memory LSTM have been extensively used in tool wear monitoring process.

In [11], a reshaped time series convolutional neural network (RTSCNN) to extract highly distinguishing features. A fully connected layer with Relu activation function and a regression layer are added to complete the prediction process of each flute tool wear. Researchers combined CNN with LSTM to predict tool wear in [12-14].

This paper proposes a framework for prediction of tool wear of CNC machine for PHM10 original dataset. The proposed framework relies on using a multi-domain feature extraction method and deep neural network regression DNN for tool-wear prediction. We benefitted from previous research in using multi-domain feature extraction and applying DNN. Applying these methods on the original PHM10 dataset was the main target of this research.

The paper is organized as follows: the next section introduces data description. Then, the main terminologies are highlighted with their latest research in the field. Discrete Wavelet Transform DWT is briefly described and Principal Component Analysis PCA after that. The following part describes the overall framework and its application on the data. A system evaluation is given at last.

2. DATA DESCRIPTION

The data we used is the PHM10 data challenge dataset for the CNC milling machine cutters [15]. Six 3-flute cutters (C1, C2, C3, C4, C5, and C6). For each of the 315 cuts made by a cutter, dynamometer, accelerometer and acoustic emission data was collected as shown in Figure 1. The data was collected at 50,000 Hz/channel. The data files (total of 6 sets of 315 files) organized in seven columns, corresponding to: force in three directions, i.e fx,fy,fz vibration in three directions vx,vyvz, AE-RMS (V) i.e. root mean square value of acoustic emission (AE). Sensors are mounted in different locations to measure these signals. The operation parameters are listed in Table 1.

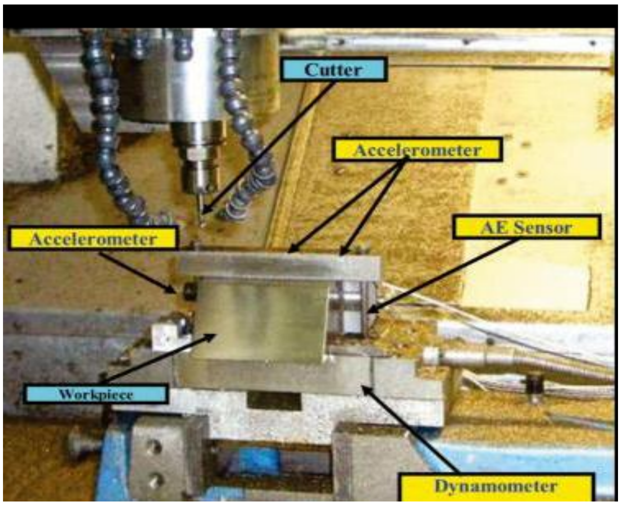

Figure 1. Sensor setup for CNC milling machine

Table 1. The operation parameters of the experimental platform

Parameters	Value
The running speed of the spindle	10,400 rpm
The feed rate in x direction	1555 mm/min
The depth of cut (radial) in y direction	0.125 mm
The depth of cut (axial) in z direction	0.2 mm

Table 2 Multi-domain features [4]

Feature	Expression
RMS	$z_{rm}\sqrt{\frac{1}{n}\sum_{i=1}^{n} z_i{}^2}$
Variance	$z_{var}=\frac{1}{n}\sum_{i=1}^{n}(z_i-\bar{z})^2$
Maximum	$z_{max}=\max(z)$
Skewness	$z_{skew=}\ E[\left(\frac{Z-\mu}{\sigma}\right)^3]$
Kurtosis	$z_{kurt=}\ E\left[\left(\frac{Z-\mu}{\sigma}\right)^4\right]$
Peak to Peak	$z_{\ p\text{-}p=}\ \max(z)\text{- }\min(z)$
Spectral skewness	$f_{skew}=\sum_{i=1} k\left(\frac{f_i-\bar{f}}{\sigma}\right)^3 S(f_i)$
Spectral Kurtosis	$f_{kurt}=\sum_{i=1} k\left(\frac{f_i-\bar{f}}{\sigma}\right)^4 S(f_i)$
Wavelet Energy	$E_{WT=}\sum_{i=1}^{N} wt_{\phi}{}^2(i)/N$

3. MULTI-DOMAIN FEATURE EXTRACTION

Feature extraction means transforming the sensor data into a number of features or condition indicators expressing the state of the machine and related to machine behavior. These new reduced set of features should then be able to summarize most of the information contained in the original set of features. As tool wear increases with time, the time-domain features are important to describe the degradation process of the sensor. The quantity of raw signal data captured by multi-sensors for tool wear monitoring is considerable and necessarily includes various forms of interference information such as environmental noise.

Many signal preprocessing techniques were used for sensor data cleaning such as Fourier Transform (FT) and Wavelet Transform (WT). Furthermore, when tool wear increases, frequency structure changes, and frequency domain features are retrieved to monitor tool wear. Time-frequency domain features are very important to conserve the energy indication of all sensors. Many researchers have made a multi-domain feature extraction model to better express the health of the machine. The details of some of these features on which we built our model are as shown in Table 2.

4. DATA PREPARATION

The WT can split a signal into a number of constituent signals known as wavelets, each with a well-defined, dominant frequency, comparable to the Fourier transform (FT), in which a signal is represented by sine and cosine functions of infinite duration. Wavelets in WT are transitory functions of short duration, that is, functions with a restricted duration centered on a certain time. The FT's difficulty is that as it moves from the time domain to the frequency domain, the information about time is lost. But, the WT have the ability of analysis in both the time and frequency domains, providing information on the signal's frequency content over time [16]. When the WT is discretized, it is now known as a discrete wavelet transform (DWT), which offers significant advantages over classic FT approaches.

5. DISCRETE WAVELET TRANSFORM FOR DENOISING

The DWT divides a signal into numerous scales reflecting distinct frequency bands, and at each scale, the position of the DWT at the critical time characteristic may be established, allowing electrical noise to be discovered and successfully eliminated. DWT can be expressed by equation (1), which decomposes a function into a set of wavelets or coefficients. It can be used as low pass filter for signal thresholding or denoising [17]. Wavelet decomposition can be made on many levels determining the number of the approximations for the signal.

$$c_{jk}=\int_{-\infty}^{\infty} f(t)\overline{\psi(t)_{jk}}dt \text{ , j,k in z} \qquad \text{Eq. (1)}$$

Where

$$\psi(t)_{jk}=\frac{1}{\sqrt{2^j}}\,\psi\left(\frac{t-k*2^j}{2^j}\right)$$

The wavelet coefficient cj,k is taken as the time-frequency map of the original signal f(t). When the cutter engages and discards the work piece, it causes some sort of noise that need to be cleared before data manipulation [18]. Some research [19] ignored the few first and last records in the cutting interval that is taken in 315 records for data denoising. Other research [20-21] used discrete wavelet transform DWT for noise removal. Soft thresholding has proved to be better in denoising tool-wear sensors in [22], thus we adopted soft thresholding in our signal denoising.

6. PRINCIPAL COMPONENT ANALYSIS PCA for DIMENSIONALITY REDUCTION

Dimensionality reduction DR means reducing the number of features or feature space expressing the signal which is a great issue in big data analysis. One of the most important methods is PCA. PCA is used to decompose a multivariate dataset in a set of successive orthogonal components that explain a maximum amount of the variance. Thus, helping to improve efficiency of the proposed method. Many studies investigated using PCA in feature-space reduction [23-24]. We used PCA in feature space dimensionality reduction.

7. DEEP NEURAL NETWORK REGRESSION

From the machine learning perspective, prognostics is a regression problem as the target (RUL) is real. Deep neural network architecture is different from classical ANN as it has deeper number of hidden layers as shown in Figure 2 and it can learn and predict target with higher speed and accuracy. The deep neural network consists of input layer, many heading layers and output layer and extremely used in prediction issues as mentioned above. Many research papers have adopted DNN for health statement of machines [25-26]. A deep neural network DNN regressor is used in this study to predict/estimate the tool wear value of the cutter to help enhance its health and may schedule for maintenance.

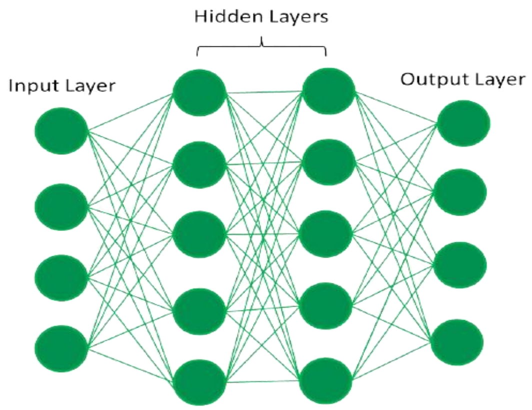

Figure 2. Deep Neural Network architecture

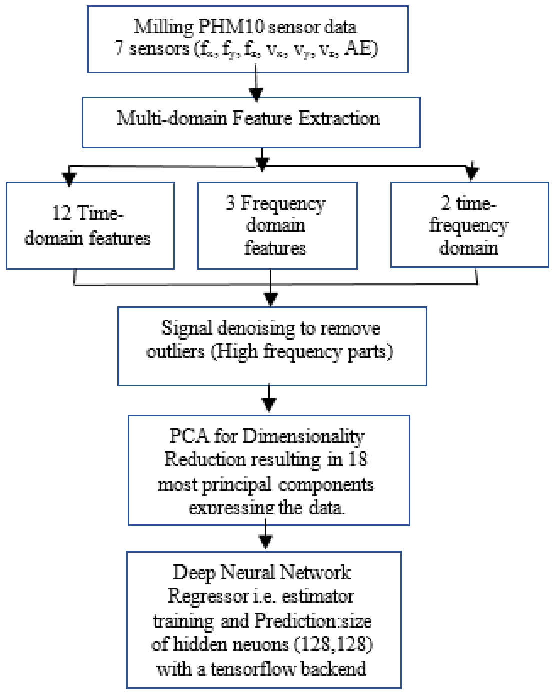

Figure 3. Flowchart of the proposed method

8. PROPSED FRAMEWORK

The tool wear of the cutter is considered a health index for the CNC machine because as the tool wear increases the RUL of the machine decreases thus must be scheduled for maintenance. We built our model on predicting tool wear of cutter using data from PHM10 data competition to predict CNC machine health. Figure 3 shows the overall framework of the proposed method. As mentioned above, many researchers studied using a number of multi-domain features so we adopted this idea in our research. We extracted time-domain features listed into Table 2 and added minimum, mean, median, variance, entropy and interquartile range IQR for all seven sensors.

In the frequency-domain we added spectral entropy and wavelet-entropy. In the time-domain the wavelet energy was added. To have a total of 17 features for each sensor. A python library named Time Series Feature Extraction Library TSFEL [27] was used to extract our muti-domain features. We extracted 17 features for each sensor to have 119 features for all 7 sensors.

Figure 4 shows 3D-plot of seventeen extracted features for a range of sensors for 315 cuts. The number of the sensor is on y-axis and the cut number on x-axis while value of corresponding feature on z-axis.

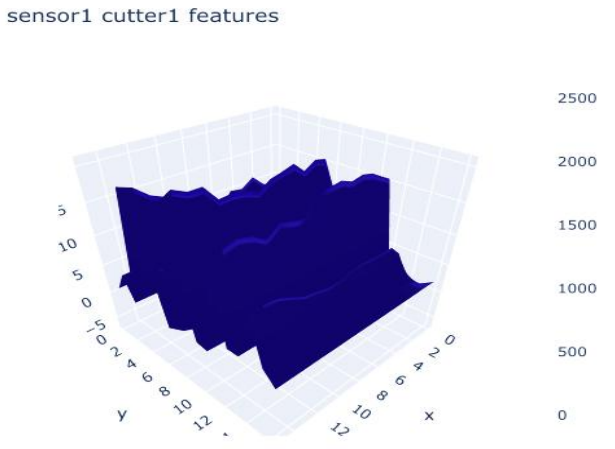

Figure 4. 3D-plot of 17 features of a number of different sensors against cut number.

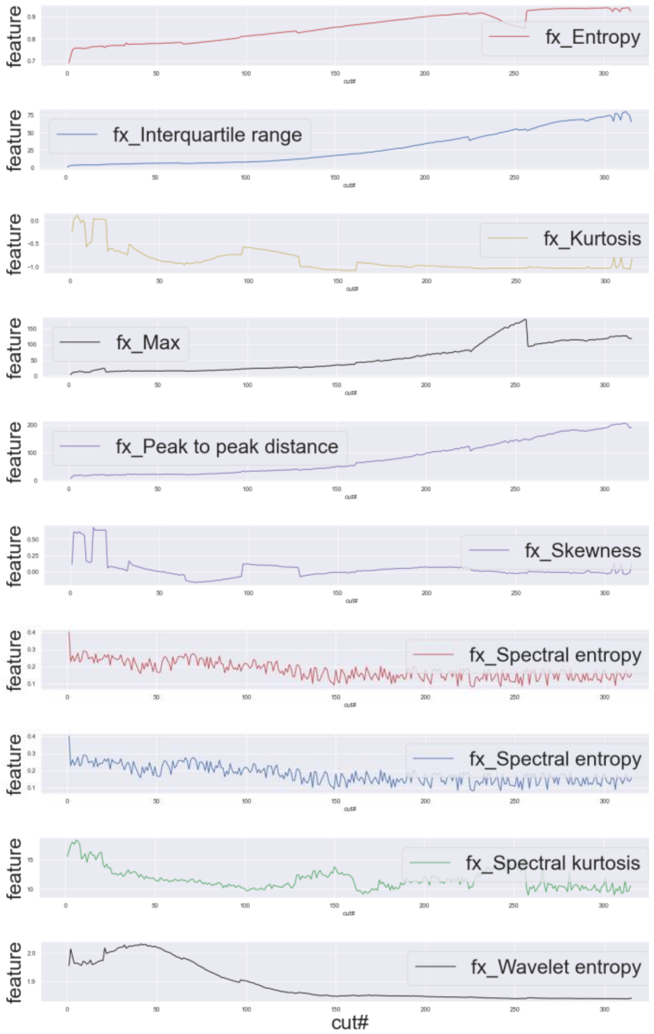

Figure 5. 2D-plot of a number of features for fx sensor against cut

Figure 5 shows a number of features for f_x sensor against run number. From top to down: f_x_skewness, f_x_spectral entropy, f_x_spectral kurtosis, f_x_spectral skewness, f_x standard deviation, f_x variance, wavelet energy and wavelet entropy. We adopted soft thresholding in our signal denoising. As an example of our sensors, Figure 6 shows the original and the reconstructed signal. When using PCA for dimensionality reduction, one or more of the smallest components are deleted, resulting in a lower-dimensional projection of the data. Thus, preserving the maximum data variance by the principal components of the data. This may be discovered by examining the cumulative explained variance ratio as a function of component number.

Figure 7 shows the cumulative explained variance of 119 features to conclude that about 20 features or less cover around 98% percent of original variance. We fitted the data to conserve more than 0.98 of its variance to reduce the dimension of features to 18 features. Data is first standardized using Eq. 2.

The reduced dataset consists of 18 signals and a target value for the wear data. Figure 8 shows some of 18 features selected by PCA against cut# on x-axis.

We constituted the training dataset from 3 cutters C1, C4, C6 which we have a wear value for them and eighteen components extracted by PCA. A deep neural network estimatorregressor is used with a tensorflow backend.

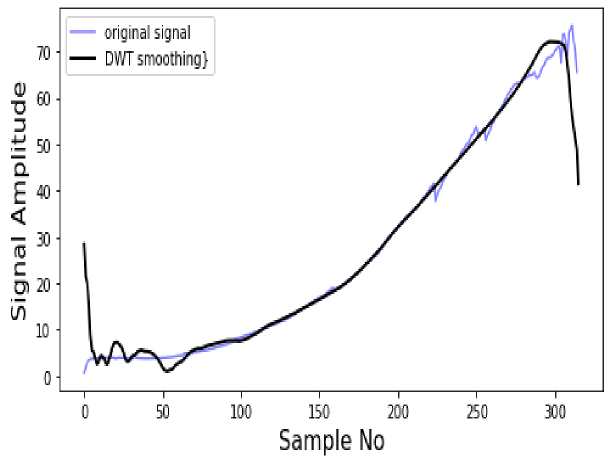

Figure 6. Original and reconstructed signal after soft thresholding.

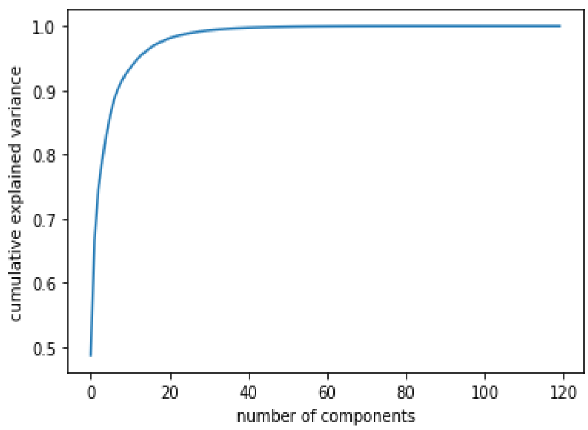

Figure 7. Cumulative explained variance for 119 features

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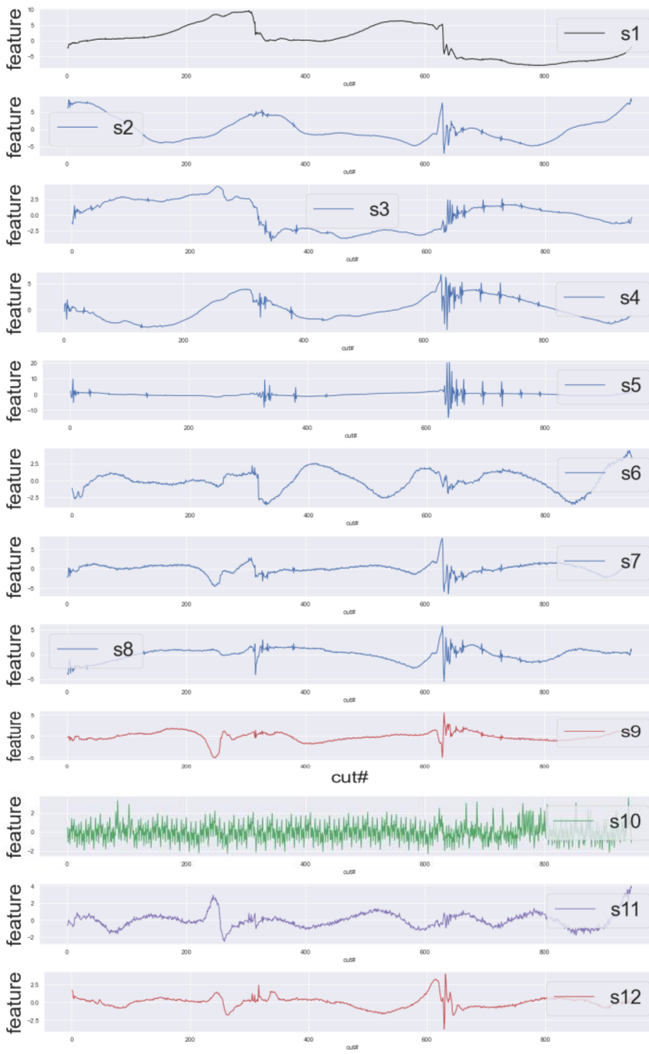

Figure 8. Some of Eighteen PCA selected features along the whole dataset

A train-test split is used to evaluate the training process. After training the model, it is used to predict the tool wear values. Figure 9 shows actual value of wear and the predicted value for C1. It shows only a part of the values because the figure is very big. It shows the predicted wear and actual wear values on some limit of the test dataset. The cut# on x-axis and tool wear on y-axis.

$$x_{new} = (x - x_{mean}) / \sigma \qquad (2)$$

where σ is the standard deviation number.

9. SYSTEM EVALUATION

The proposed method has led to a loss score (mse) of about 377 away better than [the best score (5500)] at 2010 leaderboard [28]. But, needs better improvements in respect to mean absolute error MAE value and also this loss value needs to be further reduced. Thus, we need further research to use other deep learning architectures and add an optimization part or other new trends in the field.

10. CONCLUSION

The PHM society has held many competitions including PHM10 concerning CNC milling machine cutters data for tool wear prediction. Multi-domain features were extracted using TSFEL python library. The cutter data need to be de-noised so DWT was used in this research paper to remove high-frequency noise. PCA was applied for dimensionality reduction of the extracted features and proved that the increasing the feature space is not necessarily useful as we reduced our feature space to better express the target data. We extracted the most principal components saving most of the data variance. 18 new sensors are used to express the target data. A DNN regressor is used to predict tool wear values. A comparison between actual and predicted is held. The error between actual and predicted values of wear proves that DL methods are away better earlier methods used for prediction in the PHM10 competition. The method need to be further developed to include an optimization criterion to enhance error which open new eras for research.

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Conflicts of Interest:

The authors declare that there is no conflict of interest.

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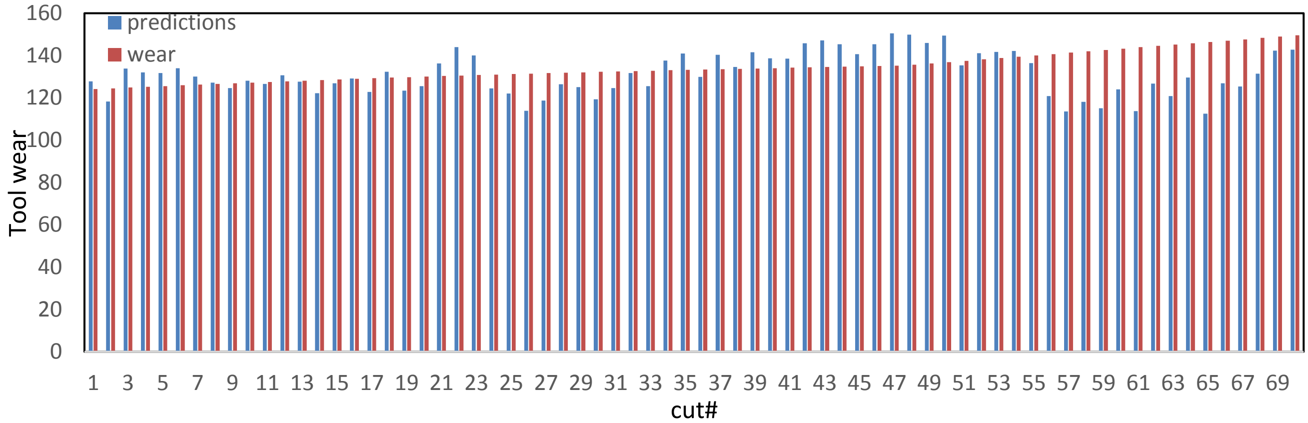

Figure 9. Comparison between Actual and Predicted value of wear against cut# for certain limit of the test dataset

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