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Remote machine mode detection in cold forging using vibration signal

Andrew Glaeser^a, Vignesh Selvaraj^a, Kangsan Lee^{a,b}, Namjeong Lee^{a,b}, Yunseob Hwang^{a,b},
Sooyoung Lee^{a,b}, Seungchul Lee^b, Sangkee Min^{a,*}

^aUW-Madison, 1513 University Avenue, Madison, WI, 53706, USA

^bPOSTECH, 77 Cheongam-ro, Nam-gu, Pohang-si, Gyeongsangbuk-do, 37673

Abstract

Detecting machine mode can allow smarter process monitoring systems and more accurate fault prediction without external information. A remote machine monitoring system was installed on a cold heading machine in the factory of an automotive fastener manufacturing company. The process monitoring system was non-intrusive and was designed to measure vibration. The end goal of the study was to predict tool wear, but part classification was required first, as the machine produced multiple parts which produced different vibration signals. The collected vibration data was processed using wavelet transform and passed through a convolutional neural network for part classification. This method achieved part classification accuracy as high as 86% when looking at data for a 1-month period. The results show that meaningful classification features are present in the data using the process monitoring system as designed.

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1. Introduction

Smart manufacturing is a term coined to describe the recent, and future, advancement in manufacturing through use of interconnected technologies. Smart manufacturing can be applied at high levels to integrate multiple business areas and maximize efficiency. This type of application requires a significant investment and a restructure of network and technology to build the appropriate platforms [1, 2]. As such, the full application of Smart Manufacturing may not be reasonable for small, to medium size, enterprises. When broken down, however, Smart Manufacturing consists of several pillars, some of which may be attainable at less cost and minimal factory overhaul. Kusiak [3] defines smart manufacturing in terms of six pillars: data, manufacturing technology and process, predictive engineering, material, sustainability, and resource sharing and networking. Predictive engineering focuses on anticipatory, rather than reactive, action and planning based on digital representations. Building a digital representation of a manufacturing process can allow mechanical diagnostic and failure estimation, leading to

autonomous manufacturing and efficiency upgrades. As a pillar of Smart Manufacturing, predictive engineering can integrate business areas such as, supply chain, manufacturing, marketing and transportation, but in the context of this paper, predictive engineering is applied to a specific manufacturing process. Predictive engineering at a process level uses real-time monitoring, and machine learning models, to predict an outcome. The outcome depends on the application, but examples can include tool wear, tool failure, power consumption, and part defects.

Several studies have verified the validity of predictive engineering through process monitoring in various applications. Rmili et al. [4] monitored vibration signal during a turning process to predict tool wear. It was shown that the change in mean power, extracted from the vibration signal over time, correlated to tool flank wear. Wang et al. [5] used force measurements to predict tool wear during a milling operation. Results were compared using both relevance vector machine (RVM) and support vector machine (SVM) learning algorithms. RVM out-performed SVM, but both algorithms classified tool wear during the milling of a titanium alloy. Nouri et al. [6] used force coefficients, calculated from process parameters, to predict tool wear for end milling. Statistical calculations, based on moving average, were shown to correctly classify tool wear. Wu et al. [7] monitored vibration to build a predictive maintenance model for rotational equipment using neural networks. Behrens et al. [8] monitored acoustic emissions to identify crack formation

* Corresponding author. Tel.: +1-608-262-1993

E-mail address: sangkee.min@wisc.edu (Sangkee Min).

during cold forging of drive bevel gears. It was shown a spike in acoustic emission indicated a crack in the product. Huang et al. [9] employed a Probabilistic Neural Network (PNN) tool breakage detection system to detect tool failure using force measurements and process parameters. Due to the learning capability of a PNN, failure data was used to continuously retrain the model, increasing its detection accuracy.

Predictive engineering can be applied to many types of operations, but one area with further potential is in cold forging. A recent interview with a cold forging company, revealed the need for such application. For a particular part, roughly 10-20% is scrapped due to defects. It is not uncommon for parts to be produced in the millions over a 1-year period. Given a rough order magnitude estimate of 2 million parts per year, at \$0.20 per part, scrapped parts could cost up to \$80,000. Additionally, when scrap rate is high for a part, the quality control and inspection process is drastically increased, adding costly man hours to overall production time. This highlights the need for a system able to predict and detect part defects during the forging process. Accurate detection and prediction can reduce scrapped parts, unplanned down time, and added inspection time. Predictive engineering can provide a solution.

This paper will focus on the application of predictive engineering in the manufacture of automotive fasteners. In cold forging, raw stock material is shaped into the desired geometry through blunt force. Due to high loads exhibited on tooling during cold forging, tool failures are not uncommon, and products are subject to cracking and other defects. The process of shaping the head of a fastener is known as cold heading. A cold heading machine forms the geometry of the fastener head through use of dies and punches. Tool failure in cold heading occurs in two dominant modes: punch failure and die failure. The major failure mechanism is fatigue fracture [10]. Other failure mechanisms include over-stressing, abrasive wear, and adhesive wear [11]. Some cold heading machines are equipped with a force monitor to detect tool failures based the values exceeding set thresholds calculated through statistical analysis. However, there are times when a small crack in the tool, or other failure, goes undetected, causing parts to be produced out of tolerance. Parts are usually produced by the thousands, so when this type of fault occurs and is not detected, the result is often costly. Further costs are incurred due to downtime required for die repair or replacement. The process is further complicated by defects in stock material. Any void or discrepancy in stock material will cause a defective part.

In an effort to detect die wear and subtle die failure, a non-intrusive process monitoring system was installed in a cold forge manufacturing factory. The intention of the system was to predict die wear and die failure, but it was observed there was a need to classify part number. The machine used in the study was capable of running different part numbers with unique geometries and tooling. In order to understand tool wear, the type of tooling needed to be known. The part number information was available through the company's resource planning data, but tooling information was not. The part number needed to be classified so the tooling could be identified. Our approach was to classify the parts produced on the machine based on vibration

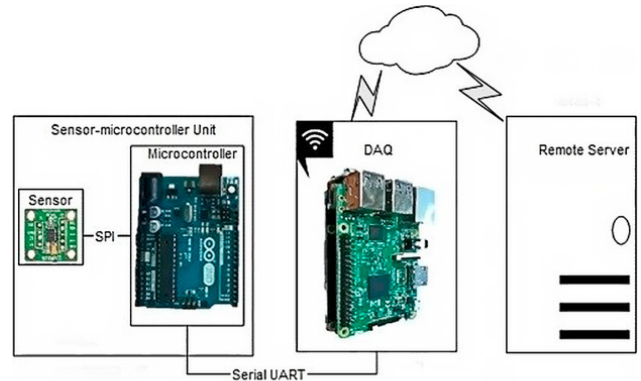


Fig. 1. A block diagram of the data collection system installed on machine including communication protocols between devices.

signal. Each part had a unique vibration profile which enabled it to be distinguished from other parts produced on the same machine. To our knowledge, this is the first application of acceleration in the monitoring of a cold heading process and is novel in the use of a convolutional neural network (CNN) for part classification.

The remaining portions of this paper discuss the development of a machine part classification system based on vibration signal. The structure of this paper is as follows. In section 2, the process monitoring system and data transfer method is developed. In section 3, the data processing and image data is constructed, and the CNN is developed. In section 4, a 1-month period of data is analyzed. Six different parts were produced during the 1-month period; therefore, six different classes were considered for classification. Algorithm training was conducted for two different training lengths and tested over multiple days. In section 5, possible explanations for the observed results are discussed. In section 6, some meaningful conclusions were drawn.

2. Process monitoring system

The monitored cold heading machine followed a two blow, one die process, meaning, two strokes were required to form the product but only one die. The first stroke created an upset on the material and the second stroke created the final geometry. The upset is an intermediate forming step in which a simplified shape of the final geometry is formed. This step is used to aid in crack prevention by reducing the total amount of material formed with each stroke. The machine was capable of cycles times as high as four parts per second. The machine cycle time and applied loads were consistent across all parts. The only available network on the shop floor was wireless. The system was designed around the use of a Wi-Fi network.

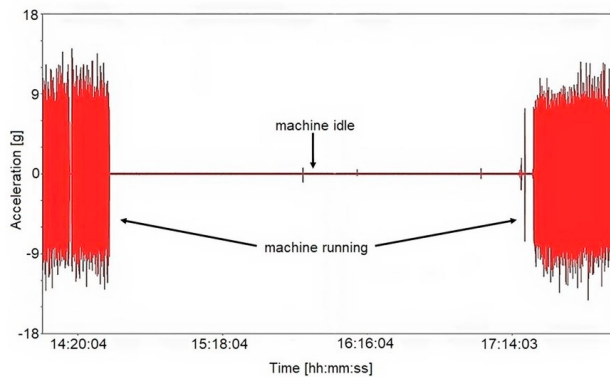


Fig. 2. Plot of the raw signal data collected by the system. The magnitude of the raw signal provides clear indication of when the machine is running and when the machine is idle.

2.1. Sensor and micro-controller

The sensor used in this system was a three-axis digital accelerometer. The accelerometer had a range of $+16g$ to $-16g$. The accelerometer was controlled by a micro-controller, which queried data based on a set sampling rate of 1650Hz . The sampling rate was specific to the sensor model and was determined from the data sheet to be the maximum rate for the chosen hardware. It was verified that the clock frequency of the micro-controller was sufficient to query the data from registers in the sensor at the required sampling rate. This was done to ensure the sampling train had equal width, which was important for future data processing. The machine produced parts at a rate of 4 parts/second. The chosen sampling rate allowed for ample data samples between machine strokes. The sensor and micro-controller unit were installed inside a protective metal case. The metal case was necessary due to the operating conditions around the forging area. The metal case was designed to facilitate cooling through vents. The unit was located on the machine as close to the forging area as possible and secured using epoxy. Due to limitations in the wireless network, real-time data transfer was not possible at the chosen sampling rate. Therefore, an intermediate Data Acquisition Device (DAQ) was used to temporarily store the data. Data transfer was done through a low bandwidth wireless network.

2.2. DAQ

The DAQ built for this study was a 200 GB external hard drive, coupled with a Raspberry Pi. The Raspberry Pi received data through serial universal asynchronous receiver/transmitter (UART) from the micro-controller and stored each value in the hard drive. Every 24 hours, the device sent the stored sensor data to a remote server, via Secure Copy Protocol (SCP), and cleared the hard drive memory. The machine was run in a two-shift system, so there was a time each day when the machine was idle. The data was transferred to the remote server during this time. The DAQ was placed inside a custom 3D printed protective case and located away from the sensor location. The

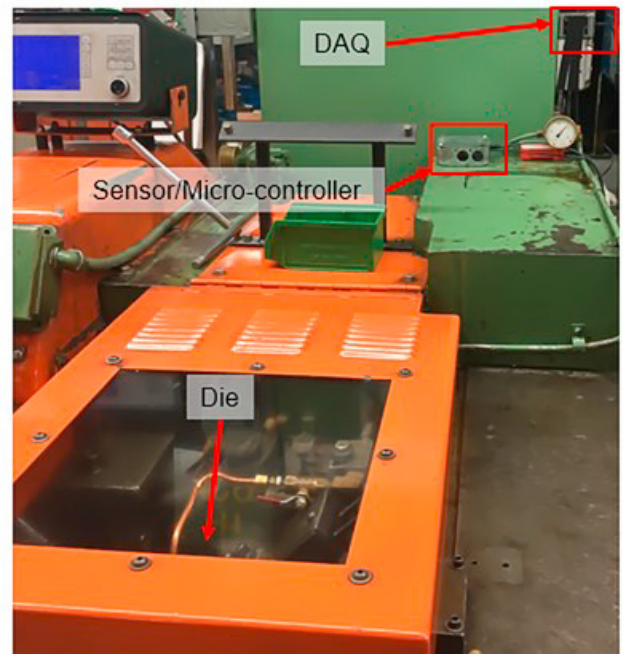


Fig. 3. An image of the installed system at the factory. The sensor-microcontroller unit was installed on the machine and the DAQ was located in close proximity. Both the DAQ and micro-controller were installed in a location chosen to minimize machine operator interference.

location was chosen to safeguard the electronics from running conditions of the machine. A diagram on the set-up is shown in Fig. 1.

The ideal location for the sensor was on the forging die, however, due to the space constraints around the die, this was not possible. Therefore, the sensor was located in an area, on the external of the machine, where the signal was strong. This location did not interfere with daily operation of the machine. It was verified that the data collected at the chosen location was meaningful before moving forward with part classification. Fig. 2 shows the raw acceleration signal of the machine over a time period. From the figure, it is clear, based on the magnitude of the signal, when the machine is running, and when the machine is idling. Although basic information, it was decided this data contained meaningful enough features to move forward with part classification. Fig. 3 shows where the sensor is located relative to the forging die.

3. Data processing and part classification

Recent literature highlight the success of CNN when classifying images [13, 14, 15, 16]. Based on this success, CNN was chosen as the algorithm for part classification. In order to get image data from raw vibration signal, the data required preprocessing. In the mechanical engineering field, short-time Fourier transform (STFT) is frequently used for implementing CNN. Wavelet transform is also a powerful tool for frequency im-

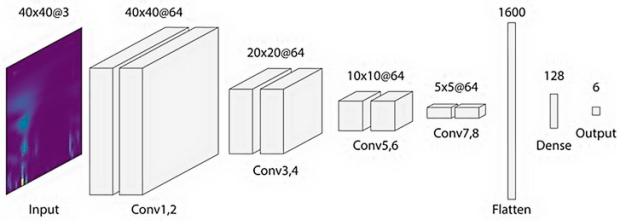


Fig. 4. Structure of Convolutional Neural Network used in this study.

age creation. STFT often outperforms wavelet when the signal data is reciprocal (gears, bearings, etc). Wavelet performs better when the signal varies significantly or is highly dampened (ex. vibration is offset by the next vibration). Wavelet is also powerful for preprocessing data when the signal is noisy [12]. Both STFT and wavelet transform were attempted for data preprocessing. The signal obtained had a low signal to noise ratio (SNR), indicating the signal was noisy. As such, wavelet outperformed STFT when classifying part numbers, so wavelet was the chosen method. The type of wavelet used was Morelet wavelet. The Morlet wavelet transform is defined by equation 1 [12].

$$\psi(t) = \exp(-\beta^2 t^2 / 2) \cos(\pi t) \quad (1)$$

The resulting image was 59x300. This image was resized to 40x40, as the CNN was built for 40x40 sized input images. The final input image was 40x40x3, corresponding to x, y, and z axes. The images were used to train, and test, the CNN algorithm.

The CNN was constructed using eight convolution layers, with three batch normalization in the pooling layers. The structure is detailed in Fig. 4. The CNN was developed during this study using 2700 wavelet images for training, and an additional 300 images for testing. We trained 50 epoch with a learning rate of $5e - 4$. In deep learning, an epoch is defined when the data set it passed through the neural network one time. The learning rate defines the rate of change in the parameters between each update.

CNN is a method of supervised learning, as such, data labeling is required for training. In order to label the signal data, resource planning data was provided by the factory. The resource planning data provided the date and time of the different part numbers produced on the machine. Using this data, we were able to label the raw signal data with a part number. On days when two different parts were run, a specific code in the resource planning data indicated when the transition occurred. An example of this is shown in the Fig. 5. Using this method, all data was labeled according to part number. 6 different part numbers were produced over the 1-month period that was analyzed, so 6 classes were used for classification.

The entire data flow is shown in Fig. 6. Data from the machine was stored and transferred to a remote server, where it was processed using wavelet transform. The resulting image was passed into a CNN and the output was part classification.

4. Results

It was assumed that the vibration signal would be consistent for the same part under the same conditions. Two pool sizes were chosen for comparison. Roughly 1 hour (52 minutes) was thought to be a large enough segment to capture the features of each part, and served as one pool size. The other pool size was chosen to be 1-day. The cycle time of the machine was 4 parts/second, so the data interval was chosen to capture one machine stroke, or 0.2 seconds (300 samples). 0.2 seconds was also used because it was lightweight for future real-time computing applications. Using the pool size of 52 minutes and interval of 0.2 seconds, part classification accuracy reached 100% when testing data from the same data pool as the training data. However, when passing in data from outside the data pool, the part classification failed.

Table 1. Results from CNN classification

Pool Size	Segment Size	Accuracy in Training Pool (%)	Accuracy outside Training Pool (%)
52 min	0.2 sec	100	Failed
1-Day	0.2 sec	Failed	Failed
1-Day	1 sec	96	86

When expanding the pool size to 1-day of data, the pool data was filtered to exclude machine idling time. Initially, the same

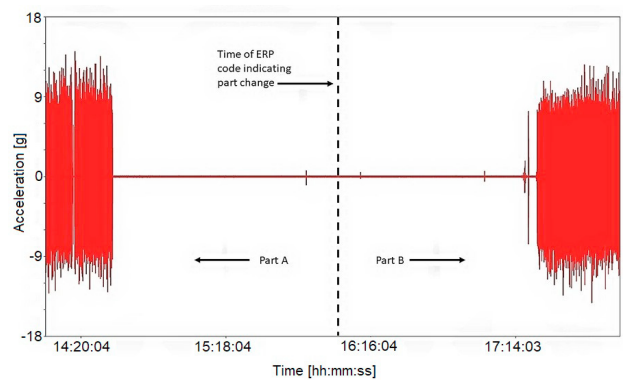


Fig. 5. Example of how the ERP data was used for data labeling. The ERP code for part change was scanned at the time indicated by the dotted line; signal prior to that time corresponds to part A and signal after corresponds to part B.

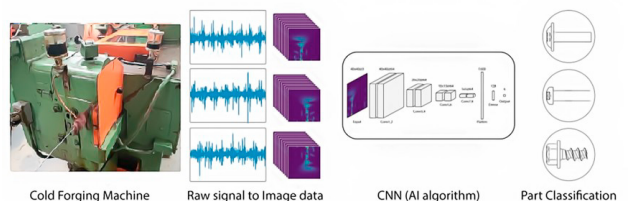


Fig. 6. Methodology of part classification from cold forging machine to final output.

data segment of 0.2 seconds was chosen, but the results showed poor accuracy. Therefore, the segment was expanded to 1 second (1600 samples). With these parameters part classification accuracy reached 96% when testing data from the same data pool as the training data. When passing in data from outside the training pool, the part classification reached 86% accuracy. The results are summarized in Table 1.

The lower accuracy when testing data from outside the training data pool suggests that the signal varies over time, even when running the same part with no recorded external changes. This is supported by the poor classification accuracy observed when using 1-day data pool size and 0.2 second segment size. Additionally, part classification accuracy decreased when using a larger pool size, compared to a smaller pool size, when testing data from within the pool data, but significantly increased in accuracy when testing data from outside the data pool. Possible explanations of this are discussed in section 5. The results can be considered acceptable for classifying part number, as it indicates, the designed system and chosen method of data analysis can determine process variation relating to part changes.

5. Discussion

There are many possible explanations for why the signal varies over time. First, in an industry setting, the same operator does not set-up the machine every time. Anything that is not automated introduces an element of human error. In the case of cold forging, as long as the produced part is within specifications, the process can change from operator to operator, including the die alignment and upset. Over the course of one month, the same part can be run on many different days. If these days are not consecutive, there is a chance the set-up will not be the same. Any slight change in the process can lead to signal variation, which can result in inaccurate classifications. Second, tooling is typically used until it produces parts out of specification. If, at the end of the job, the tooling is still functional, it

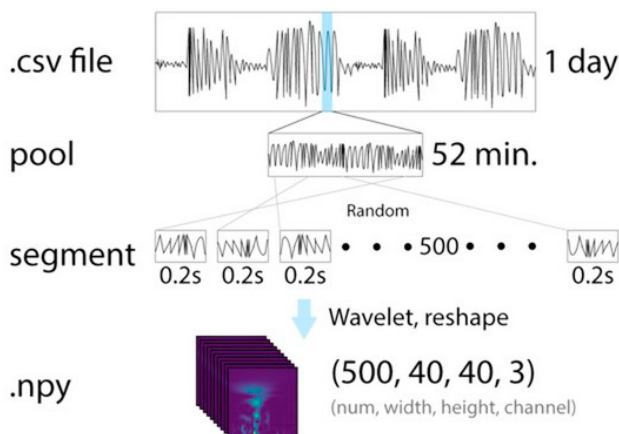


Fig. 7. Schematic of the data pre-processing sequence for a 52 minute training pool size and 0.2 second segment size.

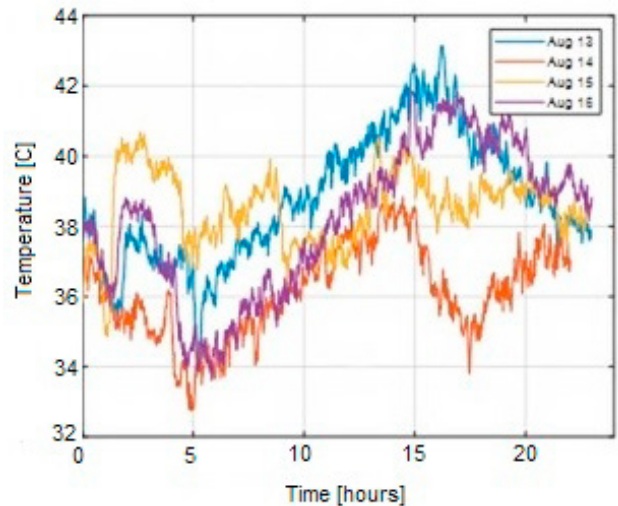


Fig. 8. Temperature data from four days included in the study. The temperature data reflects the temperature where the sensor is located. The temperature ranges observed fall within the operating temperature of the sensor, but may cause drift in the sensor readings based on the sensor data sheet.

will be used again on a different job. Because of this, tool condition is unknown, and a tool that is significantly more worn than another tool could be reused for new jobs. It is hypothesized that a change in tooling condition would impact vibration signal, therefore, impacting part classification accuracy, but further testing is required to verify. Third, external parameters that are uncontrolled in a factory could impact the sensor reading. One such parameter is temperature. It is known that temperature variation can impact sensor readings. Fig. 8 shows temperature variation for four days in August. Variations of up to 9 degrees Celsius are observed. Based on the sensor data sheet, the sensor can experience up to 0.8 mg/C offset [16]. This slight change in sensor reading may impact the accuracy of the algorithm. Further testing is required to fully understand how this impacts the output.

The failure to classify parts when using 0.2 second segments, and 1-day pool size, further supports signal change over time, but also suggests signal from machine strokes change when running the same part. A simple explanation for this is the stock material. The material is supplied in a large coil, and it is not uncommon for there to be small voids or other defects. Any difference in the material could alter the vibration profile, indicating to the algorithm a different part number.

The observed differences in part classification accuracy between the two pool sizes is most likely due to the variation captured by the pool. Greater variation can be observed in larger data pool sizes. Since the training data is randomly selected there is a chance the training data will not capture all of the signal variation for any given part. If training data does account for all variation found in the pool data, it can be expected that classification accuracy will decrease. However, the larger pool data outperformed the smaller pool data when testing data from outside the pool. The increase in accuracy, when increasing the

size of the pool data, shows that the model can account for variation in signal if variation is captured in the pool data. This, again, is mostly likely due to a greater amount of variation in the pool data available to train from. This also suggests that the variation in signal over time may not be a significant factor if the pool size is large enough. Future work is required to make the system more robust and account for larger variation in signal among the same parts. To make the system more robust, we will likely explore different sensor locations to reduce any noise that may be present, increase the training data available by running controlled experiments, and improving the hardware currently in the system.

We were limited by the available network and chosen sampling rate. The high sampling rate made real-time data transfer inconsistent due to low-bandwidth and brief breaks in connection. Any break in connection caused a loss of data. In order to prevent data loss, the data was stored on an external hard drive at the site. This method proved effective for training and testing, but did not allow real-time monitoring. Future work will be completed to bring the system to real-time monitoring and data processing by reducing sampling rate, adding a wired connection, or exploring another method of data transmission.

We were also limited on where we could locate the sensor. The machine was relied on by the company to help fill customer orders, so the sensor could not interfere with daily operation. The chosen location was capable of capturing meaningful data, but the signal was very noisy. Improving the SNR value could increase the accuracy.

6. Conclusion

A process monitoring system was designed and installed in a cold forge manufacturing factory on a cold heading machine for the purpose of part classification. Using a CNN, part classification accuracy reached 100% when training with a data pool size of 52 minutes, segment size of 0.2 seconds, and testing within the data pool. Outside the data pool the part classification failed. When increasing the data pool size to 1-day of data, and using 0.2 seconds segment size, the classification failed. However, after increasing the segment size to 1 second, the part classification accuracy reached 96% when testing within the data pool and 86% when testing outside the data pool. From the results, we can conclude:

- Meaningful features were found in the collected data using the designed system.
- Vibration signal varied over time, even for the same part. Possible explanations include machine set-up, tool condition, external parameters and material defects.
- External parameters, such as temperature, need to be considered as a reason for signal variation.

The 86% classification accuracy does not mean that there is 13% uncertainty and that part classification is done. Rather, this refers to the degree of signal deviation. When the accuracy is 50%, the algorithm cannot differentiate the processes, which

means that the process is stable enough to produce consistent signal. This should be the case when analyzing signal from the same part number. Then, for the same part number, as prediction accuracy increases, signal deviation increases, which implicitly means several possible scenarios; one is deteriorating signal due to die wear, or some other issues, part defects, etc.

The designed system was non-intrusive, inexpensive, and easy to install. The type of system described provides an efficient method for process monitoring and can be applied to any system emitting a vibration signal. The results show the potential for the proposed methodology to detect variation in process. In this study, the process variation related to different part numbers, but future research can expand it to detect more subtle variations, such as die wear.

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