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# Confidence Machine Learning for Cutting Tool Life Prediction

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## Abstract

The work aims to develop an automatic cutting tool life prediction model for die-cuts machine at Parafix. Such model will be able to estimate how long a given tool is likely to last, in order to improve performance and productivity. This work is part of the KTP project between Parafix and University of Brighton.

**Keywords:** Tool life prediction, Conformal Clustering, predictive maintenance.

## 1. Introduction

Parafix is a long established UK based converter and distributor of self-adhesive tapes, foams, films and other flexible materials, creating complex, bespoke adhesive components for a number of market sectors. One of the challenges for Parafix is understanding maintenance scheduling and machine failure, which have previously occurred mid-job where the cutting tool broke down and subsequently required jobs to be rescheduled, impacting on delivery times.

Therefore, this project aims to utilise the input data from the recently installed pressure sensors on the die-cut machines, along with the material types and the product geometries, to develop an automatic tool life prediction model, while addressing the problem of sensor noises.

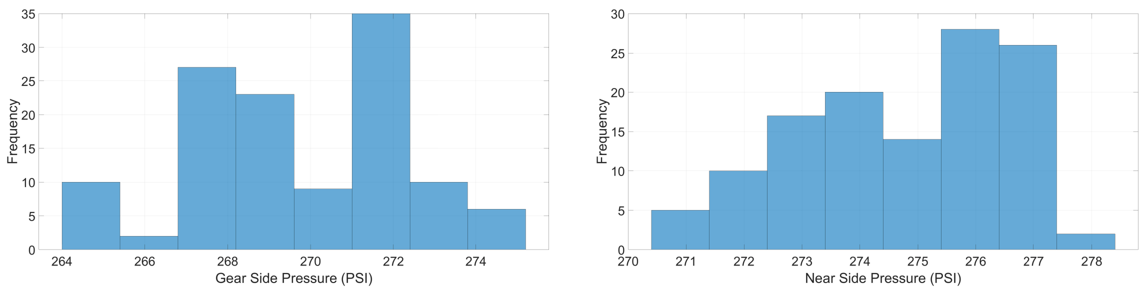
## 2. Sensor input data

The training samples come from an industry grade miniature load cell (see Figure 1), designed to operate in confined space. This load cell measures the pressure (in PSI unit) being applied by the operator on two separate points (i.e., near side and gear side) on both ends of the die-cutting machine, holding the cutting tool in place. The sensor has a sensitivity of 2.0 $mV/V$, a sampling rate of 9,000 $Hz$, and can withstand up to 2,250 $PSI$ (158 $kg/cm^2$).

However, the challenge for using such sensor is the high electrical noise (see Figure 2) at up to 12 $PSI$ (0.8 $kg/cm^2$). Therefore, there is an urgent need to develop a robust Machine Learning model that can handle such uncertainty.

(*a*) The clamp and sensor box. (*b*) The load cell.

Figure 1: Data capturing facility on each machine. The miniature load cell was installed inside the sensor box to measure the clamping force.




(*a*) Gear side pressure. (*b*) Near side pressure.

Figure 2: The histogram of the pressure measure distribution on two separate points on the cutting tool, when the machine was at rest.

## 3. Conformal predictive maintenance

Historically, most traditional Machine Learning algorithms only provide predictions, without any associated confidence information. However, when the training samples are noisy or incomplete (e.g., in our case with the pressure sensor), such information will be valuable and more informative than a simple 'Yes/No' prediction (i.e., informing the cutting tool to be replaced, only when the confidence of the prediction is high).

The assumption is that the more pressure the operator needs to apply to successfully cut the parts, the more likely that the cutting blade's sharpness has decreased and may need replacing. To assess the feasibility of our approach, we have collected 2,601 sensor samples including the gear side pressure, near side pressure, reset tally count, part count and speed, over a 3-day period. We then applied Principal Component Analysis (PCA) to reduce the data dimensionality and observed 3 separate clusters which corresponds to the data of each day (see Figure 3).

As more data will be available in the next 12 months, our work will be derived into two stages. In the first stage, we will assess the dataset to find any existing pattern, which is important for Machine Learning algorithms to work. This process involves training a Conformal Predictor on the entire dataset, to output a prediction region which can be

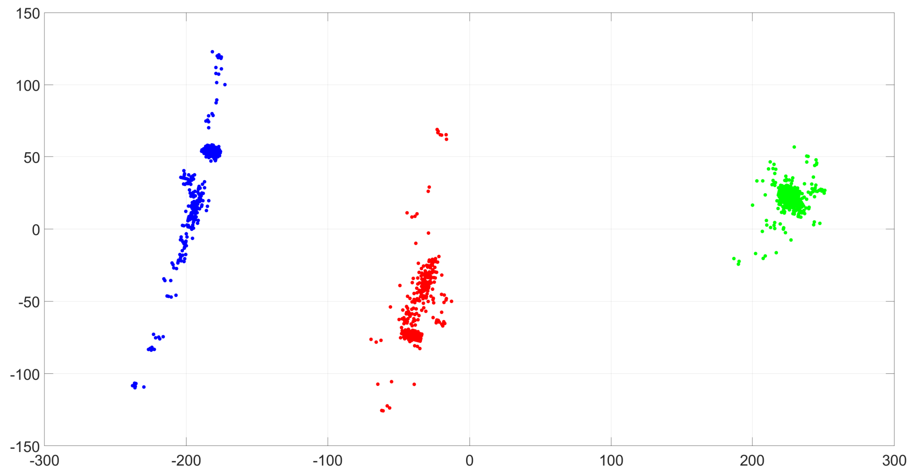



Figure 3: The visualisation of the sensor data collecting over 3 days after applying PCA, clearly indicates 3 separate clusters. Note that the operator made the big adjustment (i.e., putting more sensor pressure) at the end of each day.

divided into clusters (Balasubramanian et al., 2014; Cherubin et al., 2015). Each cluster will correspond to a different stage in the tool life cycle (e.g., brand-new, lightly used, well-used, need replacing, etc.).

In the second stage, we will build a predictive model to estimate if the tool needs to be replaced within a given time frame, using the clusters generated in the first stage. A potential method is based on k-nearest neighbours, as follows (Nouretdinov et al., 2020). Firstly, given a new sensor sample of the cutting tool in an unknown stage, $k$ nearest data points will be identified. Secondly, a majority vote will decide which cluster the new sample should belong to. For example, out of 10 nearest data points, 8 of them belong to the 'lightly-used' cluster, and the remaining 2 belong to the 'well-used' cluster; then it is likely that the tool is currently in the lightly-used state. We will verify our model's results against ground-truth labels obtained manually by the machine operator.

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