Predicting Faults in Manufacturing Production Environments

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Abstract

This research shows how condition monitoring can analyse milk filling machines within a just-in-time production environment. Fault detection is difficult as maintenance logs can be incomplete, component specifications are missing or incorrect and production comes first. Our approach requires no knowledge of the dairy filler components to quantify filler health using one class support vector machines (SVM). It does this by using a combination of time and frequency features extracted from vibration data. Furthermore, SVM training only requires artificial data.

It was found that faults on multiple components could be detected, which, if left, could have led to catastrophic failure and cost the dairy upwards of 400,000 GBP per day.

Introduction

The dairy industry is under pressure due to price constraints from supermarkets wanting to sell low cost milk and farmers who want to sell their milk for the highest price. As such, production targets dominate and maintenance only takes place when machines have, or are about to, break down. Although condition monitoring is well established in high-tech sectors such as transport and energy where safety is critical, within the food sector, it is limited in implementation and there are several cultural barriers

Literature

The available literature for condition monitoring of machinery within the food and beverage is small in number and limited in scope. Voigt et al. [1] used a model based approach to detect faults in brewery bottling plants.

Vibration monitoring is one of the key methods to diagnosing machine condition. Signal processing is a key tool for analysing vibration via time, frequency and time-frequency domain based methods. Time-frequency methods are used as they are better for non-stationary signals. Spectral kurtosis [2] and wavelets [3] have been used and will be assessed.

Figure 1: Dairy Filling Machine

Experimental Approach

Figure 1 shows the a dairy filler used in this research. The machine takes sheets of plastic, moulds them into bottles, fills them with milk and caps them. Figure 2 shows the layout of the sensors.

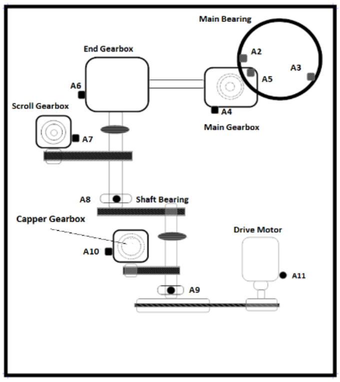

Figure 2: Sensor Layout

Health score data is computed through learning patterns of behaviour from kurtosis data computed from the vibration signal. Kurtosis, being a fourth order power, is bounded below by zero, so it was possible to create artificial data on which one class SVMs could be trained on. Figure 3 shows the principle behind the research, in that only healthy data is used for learning.

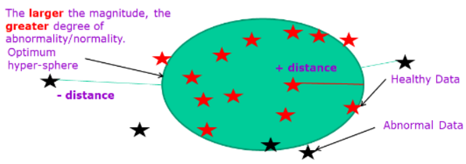

Figure 3: Learning from Healthy Data

Result and Analysis

Site 1 Filler 4 – Capper Gearbox

Fault was 'managed' during the Christmas period but worsened before replacement in March.

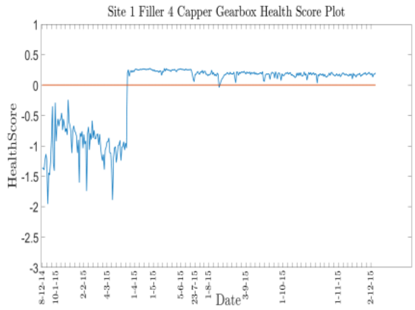

Figure 4: Health Score Plot – Capper Gearbox

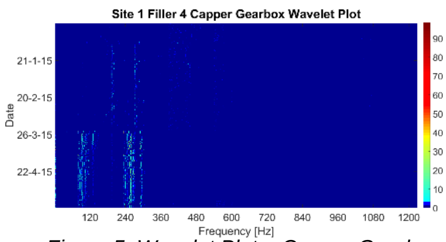

Figure 5: Wavelet Plot – Capper Gearbox

Figure 4 shows the health score plot for the capper gearbox. It experienced a fault between December and March before its repair. Figure 5 shows a wavelet analysis of the data and the change from faulty to healthy can be seen in the left hand side of the image.

Site 2 Filler 2 – Main Bearing

Fault first appeared in February and allowed enough time for a new bearing to be delivered without impacting on production targets

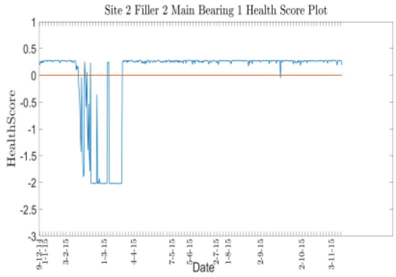

Figure 6: Health Score Plot – Main Bearing

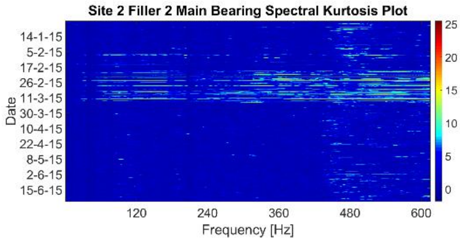

Figure 7: Spectral Kurtosis Plot Main Bearing

Figure 6 shows a main bearing fault that occurred during January to March, as seen in the health score plot. Figure 7 shows a spectral kurtosis plot and the bearing fault shows up through the blue lines in the middle of the image.

The results show that faults can be clearly detected through a variety of methods without detailed knowledge of component specifications and that there is a good correlation between the kurtosis based health score plot and the time-frequency methods

Conclusions

In environments where maintenance is not a high priority and component specification records are not readily available, the approach shows how artificial data can be used to detect actual faults. Additionally, it shows that faults are also visible via time-frequency methods such as wavelets and spectral kurtosis.

The detection of these faults enable the dairy to save >£1million GBP.

Acknowledgments

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References:

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[2] Wang, Y., Xiang, J., Markert, R. and Liang, M, Spectral kurtosis for fault detection, diagnosis and prognostics of rotating machines: A review with applications, *Mechanical Systems and Signal Processing*, 2016, 66, pp679-698

[3] Yan R, Gao RX, Chen X. Wavelets for fault diagnosis of rotary machines: A review with applications. Signal Processing 2014;96:1-15.