Sensor retrofit for a coffee machine as condition monitoring and predictive maintenance use case

Peter Burggräf[1], Johannes Wagner[1], Benjamin Koke[1], Kailashnath Manoharan[1]

[1] University of Siegen, Mechanical Engineering, Siegen, Germany
{peter.burggräf,johannes.wagner,benjamin.koke}@uni-siegen.de

Abstract. The concept of Industry 4.0 provides promising approaches to reduce downtime and increase overall equipment efficiency in manufacturing processes through interconnected devices in the industrial internet of things (IIoT). As the procurement of new IIoT-ready machines is costly, the retrofit of old machines can be an idea worth exploring. In this paper, we designed a simple experiment setup using affordable sensors and a coffee machine (due to the absence of machinery) to measure grinding vibrations and to predict the last coffee before grinder no-load. Microsoft Azure Machine Learning Studio was used to deploy machine learning techniques in order train prediction models. While prediction accuracy in this experiment was non-satisfactory, our results nonetheless indicate that retrofit is indeed a proper approach to make an older machine park smart, provided that sensors (especially their sample rate) are suitable for the application.

Keywords: Condition Monitoring, Machine Learning, Retrofit, Industry 4.0, Internet of Things

1 Introduction

With the rise of the concept of Industry 4.0 and the advent of data analytics and machine learning, **condition monitoring** to understand machine status and detect faults is considered as an important research topic [1]. In Industry 4.0, manufacturing systems include numerous sensors and interconnected devices (so-called cyber-physical systems) that form the industrial internet of things (IIoT) and facilitate the collection of large amounts of data. Data Analytics helps manufacturing firms to get actionable insights resulting in smarter decisions and better business outcomes [2]. The implementation of Machine Learning (ML) and Big Data may drive the next wave of innovation and may soon prove to be an unavoidable tactical move in achieving higher levels of optimization [3]. Some authors even argue that ML will play a major role in managerial decision-making [4].

Enabling communication and data collection in established manufacturing shop-floors, however, requires extensive capital investment in new machinery and IT infrastructure, which may prove to be a burden for small and medium-sized enterprises (SMEs). One alternative is the retrofit of older machines with sensor kits to collect machine data to

14th International Conference on Wirtschaftsinformatik,
February 24-27, 2019, Siegen, Germany

gain valuable insights. The purpose of this paper is to demonstrate the ease of retrofit initiatives by presenting an experiment setup using an affordable sensor kit and a coffee machine. The experiment involves detection of shifts in vibration frequency when the bean container runs empty to predict the last coffee. The remainder of this paper is structured as follows: first, we present relevant literature background for ML. Second, we present the experiment and results. Third, we present a discussion of the quality of results. Lastly, a conclusion and future outlook is presented.

2 Literature

ML analyses past data and makes predictions as well as decisions based on it. The machine learns to create its own logics and solutions with or without any form of human intervention [3]. There are different types of ML techniques relevant for real time scenario in a condition monitoring system. Supervised learning approaches use defined input-output tuples and require extensive training in order to make predictions for the future while unsupervised learning acts on information without pre-labeled output [5]. Classification and regression problems are the most frequently used methods in supervised learning whereas k-means clustering, auto-encoders and anomaly detection are popular in unsupervised learning [6].

Regression algorithms that are most commonly used in the domain of vibration monitoring studies include: Linear Regression [7] identifies a relation between dependent and independent variables. Bayesian Linear Regression [8] uses probability distributions rather than point estimates on generally small datasets. Neural Network Regression [9] approximate nonlinear functions of their inputs by adapting weights. Boosted Decision Tree Regression [10] creates a prediction model in the form of an ensemble of weak prediction models. With Decision Forest Regression [11], labeled set of inputs learn a general mapping which associates previously unseen independent test data with their correct continuous prediction.

As the experiment is designed as regression problem, the experiment setup (see next section) will focus on the use of regression algorithms.

3 Experiment

3.1 Setup

This experiment serves to approximate manufacturing condition monitoring by equipping a coffee machine with sensors. It is assumed that the same process applies to regular industrial applications in smart factories. Figure 1 shows the steps involved in the IoT Condition Monitoring use case of the coffee machine.

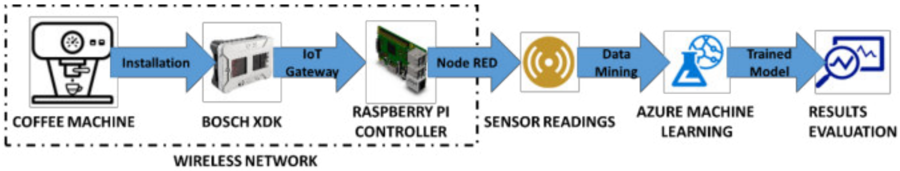

Figure 1. Coffee Machine IoT Use Case

A Bosch XDK device was mounted on the casing atop the bean grinder. Various sensor measurements (x, y and z acceleration, temperature, light, humidity, air pressure and orientation) were taken and sent to a Raspberry Pi via Wi-Fi. To reduce the amount of null measurements (machine idle), a threshold was set and measurements performed for 60 seconds. Using Node-RED, the data are transferred from the Raspberry Pi to a local server as comma-separated value (CSV) files. The CSV files were manually uploaded to **Microsoft Azure Machine Learning Studio** where data analytics and ML took place.

The raw dataset consisted of 49443 instances and 11 unique features (8 sensor measurements and 3 time stamps). The data was split into 70 percent for the training set and 30 percent for the testing. Since the dataset had over 95 percent of samples in abundant class (Idle Condition of Coffee Machine) and less than 5 percent being the rare class (Coffee Intake), it was essential to resample the training and testing datasets. Synthetic Minority Oversampling technique was used to increase the size of the rare class. Another major challenge in data preprocessing is to resolve dataset imbalance. Joining data is another complex process in the initial data preparation due to large number of missing values. Those were cleaned using Replace With Median and Probabilistic PCA (principal component analysis) approaches. Boosted Decision Tree Regression, Two-class Neural Network, Decision Forest and Bayesian Linear Regression models were trained and scored in this experiment using the feature **magnitude of vibration** as scored labels. For model testing, we deployed the model as Excel web service and provided time stamps for a typical intake cycle as input variables.

3.2 Results

With an accuracy of 62.06% (as measured by the coefficient of determination), Boosted Decision Tree Regression outperformed the other algorithms for this particular dataset. The performance of the learning algorithm strongly relies on the nature of the dataset. Other algorithms have also performed well and could be feasible options as they display accuracy slightly above 50%. When using these algorithms in regression models, slight changes in conditions between different datasets lead to wide temporal variations in the weights associated with individual features. So different temporal datasets lead to the vastly different relative importance of features, which makes the analysis of trends difficult.

4 Discussion

Good accuracy for trained models depend on several factors such as the algorithm selection, feature selection, quality, sensibility and size of data. In a classifier, 50% accuracy is considered as random guessing whereas in regression, 50% accuracy can be considered good or bad depending on the data. For the given experiment, the dataset consisted of 2472 useful data points (5%, see section 3.1). A regular coffee intake cycle held around 600 data points (average). Thus, predicting a cycle with 62% accuracy results in 228 inaccurate data points. To detect minor shifts in vibration frequency, the accuracy of 62.06% must therefore be considered non-satisfactory.

An explanation for this deficit can be found upon closer examination of the gathered data. The time stamps reveal that there is an average of 1 and a maximum of 2 measurements per second which seems to be insufficient to properly represent higher-frequency vibrations.

5 Conclusion

In this paper, we described an experiment setup to demonstrate the ease of machine retrofit for Industry 4.0 compatibility. We attempted to predict the last coffee before coffee bean depletion by collecting vibration data from a coffee machine using a Bosch XDK sensor kit and deploying ML algorithms on Microsoft Azure.

The experiment results indicate that while algorithm selection for this experiment can be considered satisfactory, data collected from this sensor are not accurate enough for this application. Using a different type of accelerometer (e.g. piezo resistive) in combination with a microcontroller with sufficiently high sample rate might help in getting better results for this use case. Therefore, as a next step, we will re-attempt the experiment using improved data acquisition. Nonetheless, we believe that this experiment highlighted that there is efficiency potential for manufacturing in retrofitting old machines through the advancement of ML and IIoT.

References

1. Moraru, A., Pesko, M., Porcius, M., Fortuna, C., Mladenic, D.: Using machine learning on sensor data. CIT 18, 341–347 (2010)
2. Lee, J., Bagheri, B., Kao, H.-A.: Recent advances and trends of cyber-physical systems and big data analytics in industrial informatics. In: Proceeding of Int. Conference on Industrial Informatics (INDIN) 2014, pp. 1–6 (2014)
3. Hoogendoorn, M., Funk, B.: Reinforcement Learning to Provide Feedback and Support. In: Machine Learning for the Quantified Self, pp. 203–214. Springer (2018)
4. Burggräf, P., Wagner, J., Koke, B.: Artificial intelligence in production management: A review of the current state of affairs and research trends in academia. In: 2018 International Conference on Information Management and Processing (ICIMP), pp. 82–88. IEEE (2018)
5. Alpaydin, E.: Introduction to machine learning. MIT Press, Cambridge, MA, London (2004)
6. Kubat, M.: An introduction to machine learning. Springer, Cham (2015)

7. Aherwar, A., Unune, D., Pathri, B., kishan, J.: Statistical and Regression Analysis of Vibration of Carbon Steel Cutting Tool for Turning of EN24 Steel Using Design of Experiments. IJMECH 3, 137–151 (2014)
8. Ye, Z., Chen, N., Tsui, K.-L.: A Bayesian Approach to Condition Monitoring with Imperfect Inspections. Qual. Reliab. Eng. Int. 31, 513–522 (2015)
9. Schlechtingen, M., Ferreira Santos, I.: Comparative analysis of neural network and regression based condition monitoring approaches for wind turbine fault detection. Mech. Syst. Sig. Process. 25, 1849–1875 (2011)
10. Burges, C.J.C.: From ranknet to lambdarank to lambdamart: An overview. Learning 11, 81 (2010)
11. Criminisi, A.: Decision Forests: A Unified Framework for Classification, Regression, Density Estimation, Manifold Learning and Semi-Supervised Learning. FNT in Computer Graphics and Vision 7, 81–227 (2011)