# IoT-based Predictive Maintenance for Smart Manufacturing Systems

Leong Chee Him*, Yu Yong Poh† and Lee Wah Pheng‡
* Tunku Abdul Rahman University College, Kuala Lumpur, Malaysia
E-mail: leongchhi@gmail.com
† Tunku Abdul Rahman University College, Kuala Lumpur, Malaysia
E-mail: yuyp@tarc.edu.my
‡ Tunku Abdul Rahman University College, Kuala Lumpur, Malaysia
E-mail: leewp@tarc.edu.my

*Abstract*—**Manufacturers have been practicing traditional preventive maintenance for many years. However, it is not cost-effective. To avoid ineffective maintenance routine and costs, manufacturers can leverage Industrial IoT and data science. This paper presents a method to optimize the manufacturing processes by using IoT-based predictive maintenance. It illustrates how an IIoT solution can be used to predict a manufacturing defect. The data is collected from multiple smart sensors stored on this welding machine. It is monitored using Statistical process control methods. Machine learning algorithms are applied to reveal hidden correlations in the data sets and detect abnormal data patterns. The recognized data patterns are then reflected in predictive models, classification approaches are used to identify the type of manufacturing processes, namely normal and welding problem. The variables that contribute the most to the failure are identified.**

## I. Introduction

Manufacturers have been practicing traditional preventive maintenance for many years. Traditional preventive maintenance has two methods: condition-based and age-based. Maintenance tasks or replacement will occur if the measure of degradation of the machine monitored is found exceeding preset threshold [1] or the operation cycle or age of the machine is longer than preset period [2]. Both methods are not cost-effective; Spare parts need to be always available and breakdown may occur before preset maintenance period. As Industry 4.0 was introduced by German government in 2011, manufacturers have moved fast to improve their process to meet up with the market expectation [3]. One of the pillars of Industry 4.0 is extension of uses of Internet to connect industrial assets, such as machines, devices, sensors, and people, or known as Internet of Things (IoT). By leveraging Industrial IoT and data science, predictive maintenance is enabled to manufacturers, which can be practiced to extend the operation cycle of machines till the end of its useful lifespan.

In this paper, we purpose a method to optimize the manufacturing process with IoT-based predictive maintenance. It illustrates how an IIoT solution can be used to predict a manufacturing defect .

This paper is organized as follows: Relevant preliminary studies are presented in Section II. While proposed method is explained in Section III, the results obtained from the method are shown and discussed in Section IV. Section V concludes the paper.

This work is supported in part by Kian Joo Can Factory Berhad.

## II. Preliminary Studies

In this section, preliminary studies are presented. Brief explanations of Industry 4.0, preventive maintenance and predictive maintenance are included in this section.

### A. Industry 4.0

As a part of a project carried out by the high tech strategy of the German government, Industry 4.0 is the term that they use to promote the computerization in Industry. Industry 4.0 is treated as the next phase of digitization of Industry. There are four pillars in Industry 4.0, they are the advancing in data accessing, computing power, and connectivity between devices; the increasing capabilities of analytic and business-intelligence; Advanced human-machine interaction with Touch User Interface (TUI), Virtual Reality (VR) and Augmented Reality (AR) systems; and the improvement in establishing connection between digital world physical world, such as advanced robotics and 3-D printing [4], [5].Industry 4.0 is not only include industry but an overall transformation where machines will be redefined in the way of they communicate with each other and carry out individual process by using intelligent engineering and digitization [6].

### B. Preventive Maintenance

Preventative maintenance is one of the most adopted maintenance strategy nowadays. Condition-based and age-based are the two major methods in preventive maintenance. For condition-based case, a machine will be monitored on its degradation measure in a constant time interval. The machine will be replaced if the measure is found exceeding preset threshold [1]. For age-based case, a machine will be replaced if the operation cycle or age of the machine is longer than preset period [2]. Preventive maintenance has significant downsides, one of them is the maintenance or replace of the machine will make the machine unavailable, which will affect the production schedule. Another downside is the spare parts need to be always available for maintenance, which increases the inventory costs [7], [8]. Besides, maintenance tasks are carried out based on the time of operation of the machine, breakdown may happen before the maintenance tasks are carried out or parts are replaced before end of their lifetime, which is inefficient in term of costs [8].

### *C. Predictive Maintenance*

Predictive maintenance is one of the maintenance methods, which fully utilizes the parts to the limit of their service life by data analysing and diagnosis on the parts and predicting their remaining service life [9]. Predictive maintenance is able to ensure the maximum time interval between maintenance tasks and minimize the occurrence and cost of unscheduled downtime by machine-train failures [8]. In predictive maintenance, by measuring and analyzing deterioration data from sensors or surveillance system, trend value can be managed, decision making can be done based on the trend value for performing maintenance tasks, and condition can be monitored through local or online system in real time [9]. In industry 4.0, predictive maintenance plays an important role to ensure and increase effectiveness of maintenance tasks [10]. While advanced data accessing, widen connectivity and advanced analytical tools are promoted by Industry 4.0, predictive maintenance is enabled as large amount of data can be monitored, pushed into analytical tools to predict machine failure, downtime, overload or any other problems [11].

## III. Experimental Study

In this section, we explain how the data is collected and the details of the proposed method.

### *A. Data Collection*

The machine used in this experiment is a can welding machine, sensors were installed in different section of the machine. The variables are described below: All the features in the data set as described below:

- Current passing the welder
- Air pressure of air circulation in the machine motor
- Vibration of the machine motor
- Pressure of nitrogen tank
- Pressure of incoming cooling water
- Pressure of incoming chilling water
- Temperature of chilling water in section B80 of the machine
- Temperature of chilling water in section B81 of the machine
- Temperature of chilling water in section B82 of the machine
- Temperature of cooling water in section B240 of the machine
- Temperature of cooling water in section B241 of the machine
- Flow rate of chilling water in section B80 of the machine
- Flow rate of chilling water in section B81 of the machine
- Flow rate of chilling water in section B82 of the machine
- Flow rate of cooling water in section B240 of the machine
- Flow rate of cooling water in section B241 of the machine

Every 500 milliseconds, a programmable logic controller (PLC) will send the sensor data to a supervisory control and data acquisition (SCADA) system, SIMATIC WinCC, via Ethernet to monitor and record in a local database. The data sets used in this experiment are the sensor data collected from April to May 2019. The failures of the welding machine during the period were recorded in manual (paper) format by the operators of the machine. There were 18 cases of failures, namely 'welding problem', occurred during the period.

### *B. Goals and Performance Metrics*

In this paper, we proposed to use one of the machine learning algorithms in Scikit-learn library, decision tree, to identify the hidden correlations in the data sets and detect abnormal data patterns. Scikit-learn uses an optimised version of the CART (Classification and Regression Trees) algorithm, which is very similar to C4.5, but supports numerical target variables (regression) and does not compute rule sets [12]. This experiment evaluate how an IIoT solution can be used to predict a manufacturing defect, by addressing the features that contribute the most to the failure. Precision, Recall and F-measure (f1-score) of failure class are used to define the prediction performance where we used to identify the features that contributed the most to the failure. While precision is the ratio of true negative to all predicted negative, recall is the ratio of true predicted failures to all true failures in the test set and F-measure is the harmonic mean of precision and recall. While different importance can be assumed by precision or recall depending on context of application, F-measure allows to take both in consideration with a single metrics [13].

### *C. Experimental Workflow*

The sensor data of the welding machine operated for hours without any failure occur was extracted and labeled as 'normal' data set. For each failure, the sensor data of 20 minutes before the failure occur was extracted and labeled as 'welding problem' data set. All the 'welding problem' data sets for the preset time interval were combined as a single 'welding problem' data set. Then the 'welding problem' data set combined with the 'normal' data set as a single data set to used in this experiment. The data set was split into train and test set with presets of features that may contribute to the failure. Data set of features was normalized if the features had different units and scales. Decision tree model was built, trained with train set and tested the prediction with test set. The presets of features used in this experiment are described below:

- All features (AF)
- Temperature of all sections in the machine (TA)
- Flow rate of all sections in the machine (FRA)
- Air pressure of air circulation and vibration of the machine motor (AP & Vib)
- Flow rate of different pair of sections in the machine
- Temperature of different pair of sections in the machine

Precision, recall and F-measure for failure class of each model were recorded and explained in Section IV.

## IV. Experimental Results

In this section, the results obtained from the proposed method for each preset of features are shown.

The values of precision, recall and F-measure of failure class for all features, temperature features, flow rate features, and air pressure and vibration features, are shown in Table I. The results shows the decision tree is able to predict failure with high value of precision and recall. Even flow rate has the highest value of recall but the value of precision and F-measure are the lowest among the feature sets. From the result, temperature seems to be the feature that contributes the most to failure with the highest value of precision and F-measure, and second highest value of recall. The values of precision, recall and F-measure of failure class for flow rate and temperature of different pair of sections in machine are shown in Table II and Table III. The result shows the temperature of section B80 and B81 has the highest value of F-measure.

TABLE I
Result of failure class prediction for different presets of features

| Features | Precision | Recall | F-measure |
|---|---|---|---|
| AF | 0.90 | 0.95 | 0.93 |
| TA | 0.86 | 0.94 | 0.90 |
| FRA | 0.54 | 0.98 | 0.69 |
| AP & Vib | 0.76 | 0.85 | 0.80 |

TABLE II
Result of failure class prediction for flow rate of different pair of sections in machine

| Features | Precision | Recall | F-measure |
|---|---|---|---|
| B80 & B81 | 0.78 | 0.16 | 0.27 |
| B80 & B82 | 0.54 | 0.97 | 0.69 |
| B80 & B240 | 0.52 | 0.96 | 0.68 |
| B80 & B241 | 0.52 | 0.96 | 0.68 |
| B81 & B82 | 0.54 | 0.98 | 0.69 |
| B81 & B240 | 0.78 | 0.16 | 0.26 |
| B81 & B241 | 0.53 | 0.95 | 0.68 |
| B82 & B240 | 0.54 | 0.97 | 0.69 |
| B82 & B241 | 0.54 | 0.98 | 0.69 |
| B240 & B241 | 0.68 | 0.19 | 0.29 |

TABLE III
Result of failure class prediction for temperature of different pair of sections in machine

| Features | Precision | Recall | F-measure |
|---|---|---|---|
| B80 & B81 | 0.86 | 0.94 | 0.90 |
| B80 & B82 | 0.91 | 0.79 | 0.85 |
| B80 & B240 | 0.93 | 0.71 | 0.81 |
| B80 & B241 | 0.78 | 0.92 | 0.84 |
| B81 & B82 | 0.92 | 0.78 | 0.85 |
| B81 & B240 | 0.81 | 0.94 | 0.87 |
| B81 & B241 | 0.92 | 0.78 | 0.85 |
| B82 & B240 | 0.94 | 0.73 | 0.82 |
| B82 & B241 | 0.78 | 0.93 | 0.85 |
| B240 & B241 | 0.92 | 0.66 | 0.77 |

## V. Conclusion

In this paper, we proposed the method of using decision tree algorithm to identify the feature that contributes the most to failure and predict the failure. The proposed method gave acceptable result of 0.86, 0.94 and 0.90 for precision, recall and F-measure respectively, and temperature is identified as the variable that contributes the most to failure while section B80 and B81 are the sections that may be the cause to failure.

## References

[1] W. Wang, "A model to determine the optimal critical level and the monitoring intervals in condition-based maintenance," *International Journal of Production Research - INT J PROD RES*, vol. 38, pp. 1425–1436, 04 2000.

[2] G. J. Glasser, "The age replacement problem," *Technometrics*, vol. 9, pp. 83–91, 02 1967.

[3] L. Bassi, "Industry 4.0: Hope, hype or revolution?" in *2017 IEEE 3rd International Forum on Research and Technologies for Society and Industry (RTSI)*, Sep. 2017, pp. 1–6.

[4] J. Lee, E. Lapira, B. Bagheri, and H. an Kao, "Recent advances and trends in predictive manufacturing systems in big data environment," *Manufacturing Letters*, vol. 1, pp. 38–41, 2013.

[5] T. K. Sung, "Industry 4.0: A Korea perspective," *Technological Forecasting and Social Change*, vol. 132, pp. 40–45, 2018.

[6] A. A. Pranab K.Muhuria, Amit K.Shuklaa, "Industry 4.0: A bibliometric analysis and detailed overview," *Engineering Applications of Artificial Intelligence*, vol. 78, pp. 218–235, 2019.

[7] W. B. Wim J.C.Verhagen Lennaert, "Predictive maintenance for aircraft components using proportional hazard models," *Journal of Industrial Information Integration*, vol. 12, pp. 23–30, 12 2018.

[8] R. K. Mobley, *An Introduction to Predictive Maintenance*, 2nd ed. Butterworth-Heinemann, 2002.

[9] J. Y. M. Saeid Mokhatab, William A. Poe, *Handbook of Natural Gas Transmission and Processing: Principles and Practices*, 3rd ed. Gulf Professional Publishing, 2018.

[10] M. Bengtssonab and G. Lundstrmb, "On the importance of combining the new with the old One important prerequisite for maintenance in Industry 4.0," *Procedia Manufacturing*, vol. 25, pp. 118–125, 2018.

[11] N. F. A. Alejandro Germn Frank, Lucas Santos Dalenogare, "Industry 4.0 technologies: Implementation patterns in manufacturing companies," *International Journal of Production Economics*, vol. 210, pp. 15–26, 4 2019.

[12] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.

[13] D. Apiletti, C. Barberis, T. Cerquitelli, A. Macii, E. Macii, M. Poncino, and F. Ventura, "istep, an integrated self-tuning engine for predictive maintenance in industry 4.0," in *2018 IEEE Intl Conf on Parallel Distributed Processing with Applications, Ubiquitous Computing Communications, Big Data Cloud Computing, Social Computing Networking, Sustainable Computing Communications (ISPA/IUCC/BDCloud/SocialCom/SustainCom)*, Dec 2018, pp. 924–931.