Improvement of Overall Equipment Effectiveness from Predictive Maintenance

Leong Chee Him[1], Yu Yong Poh[2] and Lee Wah Pheng[3]

[1, 2]Department of Computer Science and Embedded Systems,
Faculty of Computing and Information Technology,
Tunku Abdul Rahman University College
[1]leongchhi@gmail.com, [2]yuyp@tarc.edu.my

[3]Centre For Postgraduate Studies and Research,
Tunku Abdul Rahman University College
limtm@tarc.edu.my

ABSTRACT. Overall Equipment Effectiveness (OEE) has been used by manufacturers as a key metric to identify how productive a production operation is, during the planned production time. While Industrial Internet of Things (IIoT) can be leveraged with data science, predictive maintenance becomes a better option for manufacturers to maintenance their equipment. In this study, a simulation of predictive maintenance was done by using Classification and Regression Tree (CART) algorithm to predict machine failure. We also discussed the possible improvement of predictive maintenance to OEE.

KEYWORDS: Overall Equipment Effectiveness, Industry 4.0, Predictive Maintenance

1 INTRODUCTION

Equipment is the key element in a production system. The state and level of equipment can directly affect the cost, quality and productivity of a product (Zhu 2011). The critical measurement and metric of indicating such variables of equipment is Overall Equipment Effectiveness (OEE). The main purposes of OEE is to maximum the effectiveness of equipment by lower its downtime and decrease the cost of operating equipment with reaching maximum productivity (Ng et al. 2014). To maintain production stability, preventive maintenance becomes the best option for last decades. However, with the advanced technologies and the introduction of Industry 4.0, Internet of Things (IOT) becomes more available for manufacturers, and also enable predictive maintenance. By installing sensors in equipment, real-time data of the equipment can be monitored and collected for analysing with machine learning algorithm to detect future breakdown.

This paper is made on the purpose of discussing the possible improvement of OEE by using modelling of machine learning to simulate practice of predictive maintenance.

This paper is structured as follows: Relevant preliminary studies are presented in Section II. Research methodology is explained in Section III, the results obtained from the method are shown and discussed in Section IV while conclusion in Section V.

2 PRELIMINARY STUDIES

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

2.1 Predictive Maintenance

As one of the maintenance methods, predictive maintenance fully utilizes parts of equipment to the limit of their service life where by analysing and diagnosing data from sensors, and predicting parts' remaining service life (Mokhatab et al. 2018). One of the advantages of predictive maintenance is able to maximize the time interval between maintenance tasks, minimize the occurrence of unplanned downtime of equipment, and reduce the cost of repair (Mobley 2002). By installing sensors or surveillance system, status of equipment can be monitor in real-time, data can be collected and push into analytical tools to predict failure, downtime, overload or any other problems of equipment (Frank et al. 2019). With that, degradation of equipment can be tracked, trend of degradation can be managed, and decision making on maintenance tasks can be more effective by taking account of the result of data analysis. (Mokhatab et al. 2018). Predictive maintenance plays a key role in Industry 4.0, where to maximize the effectiveness of maintenance tasks (Bengtssonab & Lundströmb 2018).

2.2 Overall Equipment Effectiveness

Overall equipment effectiveness (OEE) was introduced as a core concept in Total Productive Maintenance (TPM), a manufacturing improvement that originated from Japan (Nakajima 1990, Sheu 2006). OEE is not only an operational measurement of equipment, it is also used as an indicator of improving manufacturing processes (Ng et al. 2014). OEE is calculated based on three main factors: equipment availability, equipment process performance and quality rate. The three factors measure the losses of equipment and production during operation (Nakajima 1990, Ng et al. 2014). The six major losses are time loss due to unscheduled stop, time taken to setup and adjust equipment, time loss of equipment sits idle and minor stop, slow production speed, defective product, and start-up reject (Nakajima 1990, Ng et al. 2014). Time loss due to unscheduled stop, and setup and adjust equipment, are used for calculation of equipment availability (Nakajima 1990, Ng et al. 2014). The efficiency equipment process performance are determined by using time loss of equipment sits idle, minor stop and slow production speed (Nakajima 1990, Ng et al. 2014). Losses of defective product and start-up reject are categorized as quality rate losses (Nakajima 1990, Ng et al. 2014). The ideal values for OEE components are:

- Equipment availability in 90% or higher
- Equipment process performance in 95% or higher
- Quality rate in 99% or higher
- OEE in 85% or higher

3 RESEARCH METHODOLOGY

A case study was conducted in a packaging company founded in 1956 in Malaysia. This study focuses on a tin can welding machine. It consists of input, machine and output. For input, materials such as tin foil and copper wire are loaded into the machine. The machine will roll the tin foil into a cylinder shape. For output, the tin foil will be welded with copper wire as solder. The main failure that occurs on the welding machine is welding problem, where the welding machine is unable to continuously weld the tin can to meet with the quality standards. The failure is mainly caused by overheat on welding nozzle. In this study, the welding problem is the main target for predictive modelling. In the company, the maintenance standard operating procedures for the failure are shown:

- Operator notices the failure happen.
- Operator notifies his/her supervisor.
- Supervisor confirms the failure and records the time of failure happen
- Supervisor notifies maintenance team.
- Maintenance team send member(s) to maintenance the machine.
- Maintenance team records the time taken for maintaining the machine.

Smart sensors were installed in various parts of the tin can welding machine to collect data of following aspects:

- Welding current
- Welding speed
- Temperature and flow rate of cooling water in different sections of the machine
- Air pressure of machine motor
- Pressure of nitrogen tank

The data was collected every 500 milliseconds and saved in a local database.
Decision tree algorithm in Scikit-learn was used. The decision tree algorithm used is an optimised version of the Classification and Regression Trees (CART) algorithm but does not support categorical variables as input (Pedregosa et al. 2011). In this study, we used the data collected from April 2019 to June 2019 for the decision tree model. The data were extracted by two condition: the machine was working properly for at least an hour and 20 minutes prior a welding problem happen. The extracted data were split into training set and test set for the model. The total amounts of data were 121200 for normal and 86400 for welding

problem. During the model training process, we found out the decision tree model trained with the data of temperature of cooling water was able to predict welding problem with the highest accuracy, 90 percent, among other features. Thus, we used the decision tree model in the experiment.
The data on 6th of August 2019 was used for calculating OEE in the experiment. The reason of using data on 6th of August 2019 was the downtime of the machine due to human error or failure of other machines in the same product line was the lowest on record. Thus, the calculation of availability for the machine would be more accurate. The total amount of tin foil used, wastage of defected product and good quality product were recorded.
For experimental workflow, we used the data on 6th of August 2019 to calculate OEE every 20 minutes of the planned schedule. The OEE result was used as indicator for loss of availability, performance or quality of the machine during the period. Next, we simulated predictive maintenance by using the decision tree model to predict welding problem. Then, we compared the predicted results and the recorded occurrences of welding problem for simulating welding problem can be avoided if it was predicted.

4 RESULT AND DISCUSSION

In this section describes and illustrates how predictive maintenance was used to improve the overall equipment effectiveness at the tin can welding machine in the company.

4.1 OEE

The OEE factors for the welding machine on 6th of August 2019 is shown in the table 1:

Table 1: OEE Factors

Items	Data
Shift Length	24 hours (1,440 minutes)
Breaks	(4) 15 minutes, (2) 30 minutes and (1) 45 minutes
Downtime	646 minutes
Ideal Run Time	85 pieces per minute
Total Count	33,874 pieces
Reject Count	178 pieces

The OEE calculation was done every 20 minutes and displayed in a graph by using Bokeh, an interactive visualization library in Python. However, the recorded downtime of the welding machine was mostly caused by the other machines in the same production line, where the speed of production of the other machines cannot keep up with the speed of the welding machine. The failure due to welding problems occurred two times, reported at 4.45 pm and 5.49 pm. The welding machine was stopped to operate and maintained for 10 minutes and 15 minutes. Thus, the results of OEE calculation between 4.40 pm to 6.00 pm are the focuses in this experiment. The graph is shown in Figure 1:

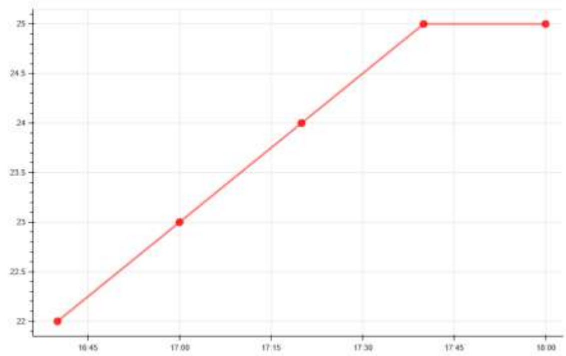

Figure 1: Graph of OEE Calculation

The decision tree model was trained with historical data from April to June 2019. By inputting the data of 6th of August 2019, the model predicted failure at 4.00 pm and 5.48 pm. Assuming predictive modelling was adopted for predictive maintenance, the maintenance team can plan the maintenance task at a suitable time before failure happen and decrease the downtime of the machine. By doing so, the availability of the welding machine can be improved due to reduced downtime, and the performance of the welding machine can be improved as the machine can be maintained and running in peak performance. The assumed results of OEE calculation between 4.40 pm to 6.00 pm is shown in Figure 2:

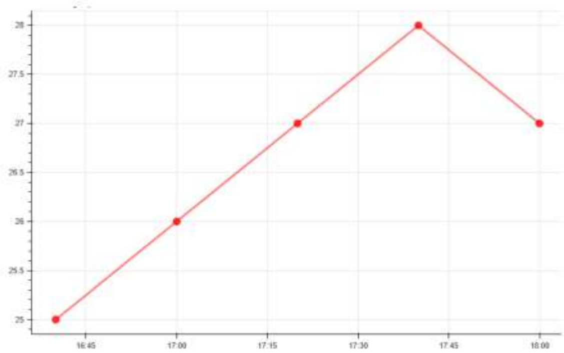

Figure 2: Graph of Assumed OEE Calculation

5 CONCLUSION

The paper proposed the method of using predictive modelling helps to improve the OEE. The decision tree model successfully predicted the happening of incoming failure, and OEE can be improved. However, the model has its flaws, including occurrences of false positive, and the downtime of the welding machine mostly due to the other machines in the same production line. In future, we will use predictive modelling on the whole production line to improve the OEE of every machine.

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