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MACHINE LEARNING APPLICATION IN PREDICTIVE MAINTENANCE ON AN AUTOMATION LINE

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ABSTRACT

The purpose of this study is to explore application of Machine Learning algorithm in the Predictive Maintenance on an Automation line. Screw height, torque and height data from Auto Gang Drive were used to train machine-learning model. Proper control of the driving process is critical for screw torque process that applied the clamp force is equally distribution. Auto Gang Driver module cycle time is 4.5 seconds, and rapid process control is required to ensure successful process. A supervised machine learning approach is applied for this study. The data were pre-processed and classified into two types of classifications, which are “passed” and “failed”. The ground truth was performed by visual inspection of the workpiece, which is a Hard Disk Drive disk clamp screw driving assembly. Two models of machine learning, Support Vector Model and Decision Tree models, were explored to compare the accuracy of the model. The result showed that Decision Tree has 100% accuracy in predicting the detection of the failure. The Decision Tree model was then deployed on the Auto Gang Driver module to monitor the screw driving process. A framework for machine learning implementation was drawn to replicate the implementation to other automation module. Future work such as monitoring of the health of the machine using data such as incoming compressed air, pressure and flow by applying machine learning can deploy predictive maintenance on the machine.

Keywords: machine learning, predictive maintenance, support vector model, decision tree.

INTRODUCTION

Predictive Maintenance is one of maintenance strategies used in manufacturing industries to forecast the reliability or failure of equipment before it happens. This allows manufacturers to optimize the production output, control cost and improves quality of end product [1-3]. With the advancement in sensors and monitoring devices, enable engineers to collect, analyses and make decision based on data and in turn put in monitoring and alert system to trigger before failure happens. Improvement in connectivity especially in devices communication with each other or to a centralized system, makes monitoring, optimizing of setting, reporting and acting on failure much easier and accessible.

With data from sensors equipment, it enables engineers to deep dive into the data and makes sense of the reliability of machine. Typically, data analysis is performed in time-series method and engineers able to analyses the performance of the machine overtime. Any trend change, or behaviour that may signify a failure behaviour, engineers will be able to classify the data in categories for historical reference. This historical reference can act as learning library to predict machine reliability. As time progresses, engineers may build up a vast library data set with different scenario from various machine to improve accuracy of the prediction.

Automation in Manufacturing

As industries continue to improve productivity, quality and reduce labour cost, automation becomes a viable option. Automation has existed since 1980s, when manufacturing industries grows especially in the United States and European continent [4]. Computing power during this period enables simple robotic movement, stores data locally in the machine and make simple pass or fail decision. During this period, most manufacturers used breakdown or preventive maintenance strategies to fully utilize their automation equipment. However, breakdown strategy creates such as high cost, quality issues and fire-fighting workplace. Spare parts that are not readily available may have to be source with higher price because machine need to be repair in shortest time. [5]. End product may be affected and quarantined. This result in lost opportunity cost, as product cannot be ship to customers and may have to scrap because it does not meet certain specification. Workplace may be chaotic, as organization may engage daily reactive activities to response to customers due to quality issues or lack of spare parts to repair the machines.

There are two widely maintenance application in manufacturing industries, reactive and preventive maintenance. Reactive maintenance is running the production line or equipment asset to the point of failure and defective parts on a machine is replace. This method pro-long the lifespan of the machine and increase the machine capacity, however it does not guarantee the quality of the product produced.

Preventive maintenance is schedule maintenance method applied in manufacturing industries. Typically, schedule maintenance requires the production lines or equipment asset stop for a certain period of time for repairs. The parts on a machine are change in regardless of whether it requires replacement or not. This method is costly and also does not guarantee that the parts produced are good quality. In a report by Multi-National Manufacturing (MNC) plant in Malaysia, where the impact to production output is estimated to be 10% output loss per day, it has following excerpt:

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a) Quality Excursion impact to cost is estimated to be $ 2.65 million US dollar per year

b) Scrap cost by problematic assembly line is estimated to be $112,000 US dollar per month

To address the problem of capacity utilization and reduce cost, Predictive Maintenance method is being investigated. Predictive Maintenance is defined as forecast maintenance and prevents equipment failure. Useful remaining life is also important part of Predictive Maintenance. Predictive maintenance method is able to predict the failure, and also the remaining life of a machine to schedule repair activity at a certain point in time.

It is expected that the impact and benefits of Predictive Maintenance system to reduce maintenance cost by 40% [6], asset maintenance uptime and machine availability improved by 15% [7], and maintenance breakdown to reduce by 70% [8].

Predictive Maintenance

The basis of Predictive Maintenance, in its essence it basically forecast the fault or error in the system of the machine and predicts the machine useful life. This is particularly different from other maintenance strategies such as Break-down or Preventive Maintenance, where machine is run until it breaks and the latter is scheduling for maintenance before the end of machine useful life. Predictive Maintenance strategy detects a foreseeable failure and forecast the machine health of its useful life. This optimizes the capacity utilization of the machine and ability to schedule for machine time for repair [9].

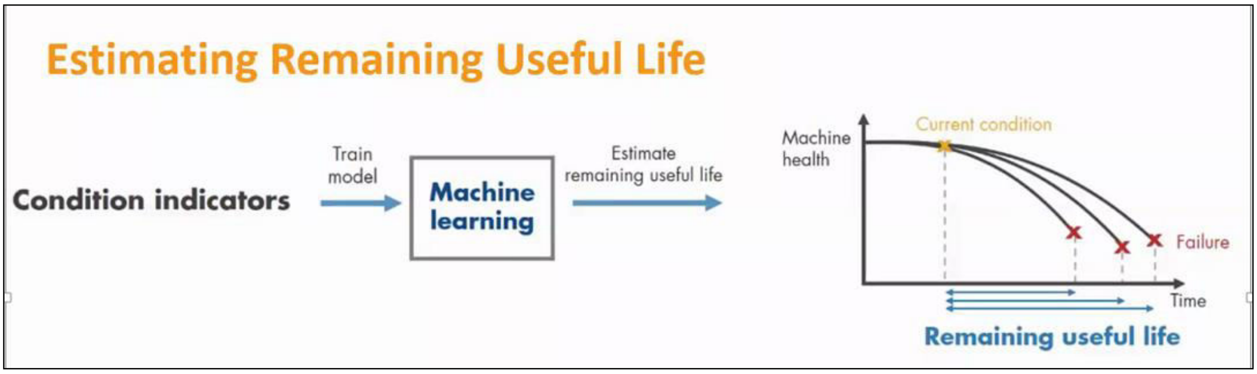

Figure-1. Conditional monitoring and machine remaining useful life [10].

In order to enable Predictive Maintenance, sensors play a crucial part in the machine system. Sensor able to measure mechanical parameters of the machine condition in the system and send the measurement in the form of data for users to interpret. Usually, the data is represented in time-series format, which it is called signal modelling. Illustration in Figure-1 represents the behavioural process of the machine and it gives users especially technical personnel a view of the health condition of the machine.

Machine Learning Application in Predictive Maintenance

Predictive maintenance, or “condition-monitoring” maintenance has been around since the 3rd Industrial Revolution with the rising used of robotics and computing system [11]. With integrated sensors build into the machine, predictive maintenance can reduce machine downtime, increase machine utilization, focus on the root cause, improve machine efficiency and in return save cost. In a way, predictive maintenance is a form of preventive maintenance or scheduled based maintenance. The different is predictive maintenance is able to forecast the “useful life” of the machine and predict when the machine health will be deteriorated and schedule for repairs. This is completely opposition from preventive or scheduled maintenance, whereby machine is down for maintenance based on fixed timeframe. There are several approaches on predictive maintenance such as data-driven, model-based and hybrid approach.

Data-driven is the use of data to learn the machine or process system behaviour. The model-based approach is the use of the ability of integrating physical understanding of the process to represent the behaviour of the machine. There are the mixed uses of both data-driven and model-based, which is known as hybrid approach. All predictive approach can use machine learning to provide effective solutions.

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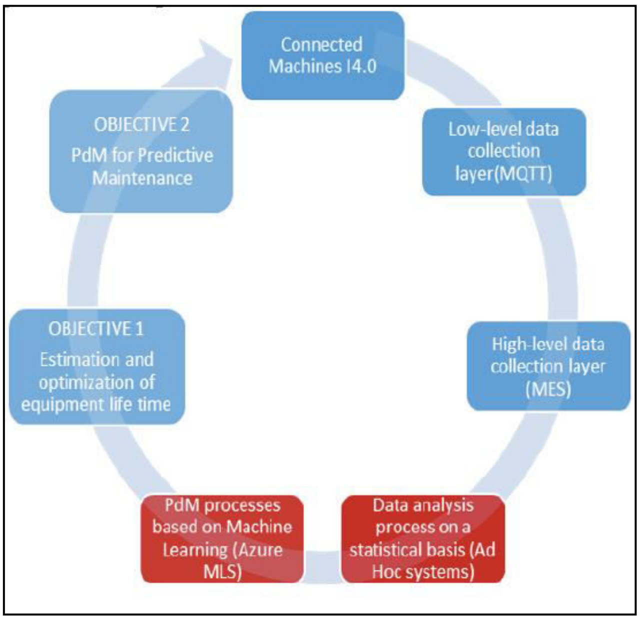

Figure-2. Diagram of activities to be performed in Predictive Maintenance.

Figure-2 shows a diagram of activities to be performed to implement predictive maintenance. Machine learning can be implemented using the data collected from machine sensor and integration with Manufacturing Enterprise System (MES). Once the data source is available, then we look at different types of machine learning algorithms that could be used for predictive maintenance. Generally, there are three types of machine learning:

a) **Fault history:** It is necessary to compile all the fault error from machine histories and its data. It is for the machine learning to develop algorithm based on fault history to learn the normal operating process and its failure scheme.

b) **Maintenance/Repair history:** The other important data source is the maintenance or repair history of the machine. This data is important to ascertain the component that is faulty, being replaced or maintenance action that was performed.

c) **Machine useful life:** Normally machine condition deteriorates over time and it is important that there are data, which contain any anomaly that could have machine performance issues at a certain period.

Once the data source is available, then we look at different types of machine learning algorithms that could be used for predictive maintenance. There are two types of machine learning, supervised and unsupervised [12]. Supervised learning trains a data model on a known input and output model whereas unsupervised learning finds hidden patterns in the input data and output classification model of data. In this study, focus would be on supervised learning as shown in Figure-3, where the predictive model based on input and output data will be developed by Weka Software application. In supervised learning, the data would require pre-processing to categories the data into groups. Then pre-process data would be input into Weka Software to generate a mathematical model for the groups.

With Weka Software, SQL code will develop to classify the data based the mathematical model. The SQL code will be deployed on the automation tool IPC system to monitor the machine health during production runs. Any fault on the machine, it will prompt alarm and error message based on the pre-process data. Any new anomalies will be input back to Weka Software to improve the mathematical model.

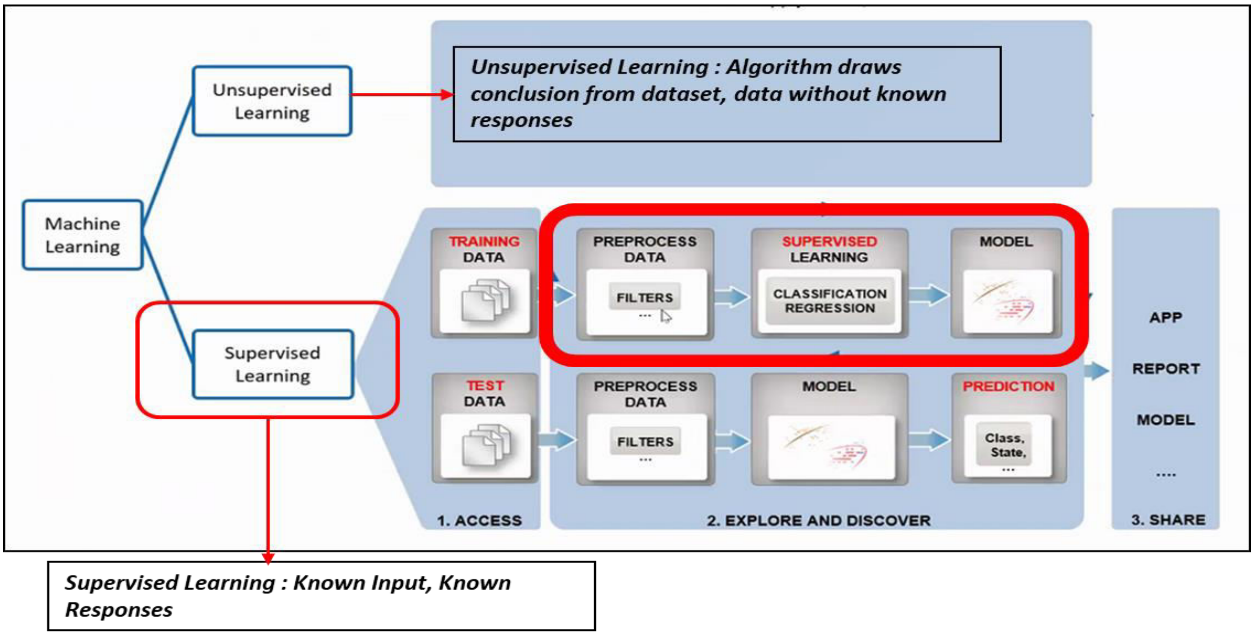

Figure-3. Supervised machine learning flow [10].

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MANUFACTURING AUTOMATION LINE

Next Enhanced Operation (NEO) as shown in Figure-4 is used as Proof of Concept for deploying machine learning predictive model. The automation line is codename NEO, it is acronym for Next Enhanced Operation. It consists of 16 modules with end-to-end total length of 16.20 meters. The out-to-out take time is 4.5 seconds. The NEO automation line uses Beckhoff Automation System as Controller for each of the modules. For Proof of Concept, the Auto Gang Driver is selected for POC, acronym for Proof of Concept to deploy machine-learning model onto the machine for process control and monitoring.

The Auto Gang Driver machine is a machine that automatically pick up six screw from a screw feeder, move in single axis to the work piece, and auto screw drive six screws simultaneously on to the disc clamp on the work piece. There are total six auto screwdrivers, with torque transducer and encoder to measure each individual screw height. The process parameters data that are of interest are Screw Final Torque, Screw Final Height and Total Rotation (Angle, in degree).

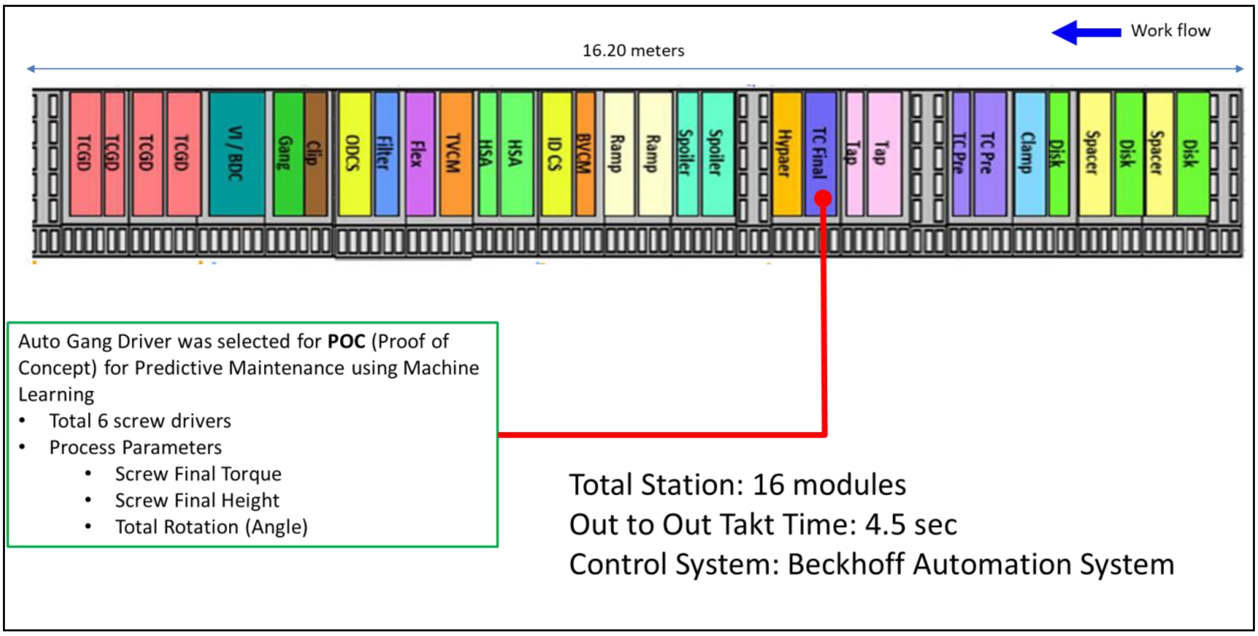

Figure-4. Next Enhanced Operation (NEO) automation line.

Auto Gang Driver Module

The Auto Gang Driver module (Figure-5) is a two-axis movement mechanized assembly module that pick up the screw from a screw presenter module. The screw presenter module is attached to the screw feeder, where there is another screw pick mechanism that pick the screws from feeder and place it onto the presenter. The screw feeder feeds the screw to the presenter when it senses that the presenter is empty. The presenter always standby with screw, so that is process cycle time is not constraint and clamp screw driving process starts when Hard Disk Drive assembly reaches the module. This is important to meet the automation take time of 4.5 seconds. The process breaks down for the Auto Gang Driver are as follows:

a) Hard Disk Drive reaches and seats on the Auto Gang Driver module - 0.5 seconds
b) Auto Screw Driver Module move down to start screw driving process - 0.5 seconds
c) Screw driving process - 1.5 seconds
d) Auto Screw Driver Module move up to standby position - 0.5 seconds
e) Hard Disk Drive departs from Auto Gang Driver module - 0.5 seconds

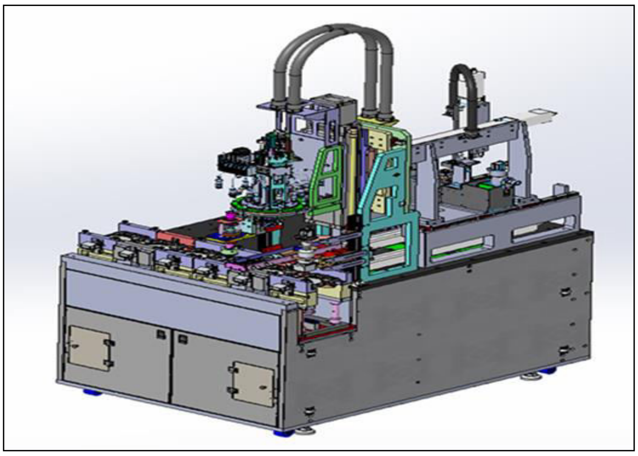

Figure-5. Auto gang driver module.

The total take time this process is 3.5 seconds. Screw feeding, picks and driver move to standby position takes estimated 1.0 second. Therefore, the overall process has to be below 4.5 seconds for a successful process. The

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effective screw driving time is 1.0 seconds, and process control including monitoring has to be at rapid pace. Figure-6 illustrates the screw feeding process and Figure-7 shows the torque profile of the Auto Gang driver screw driving process.

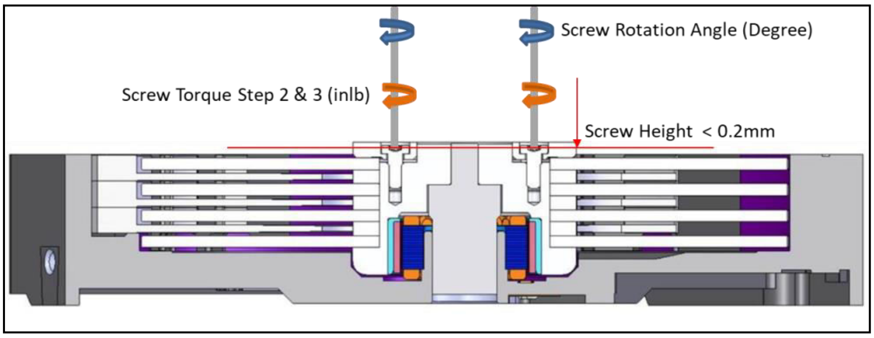

Figure-6. Cross section of hard disk drive assembly and screw driving process.

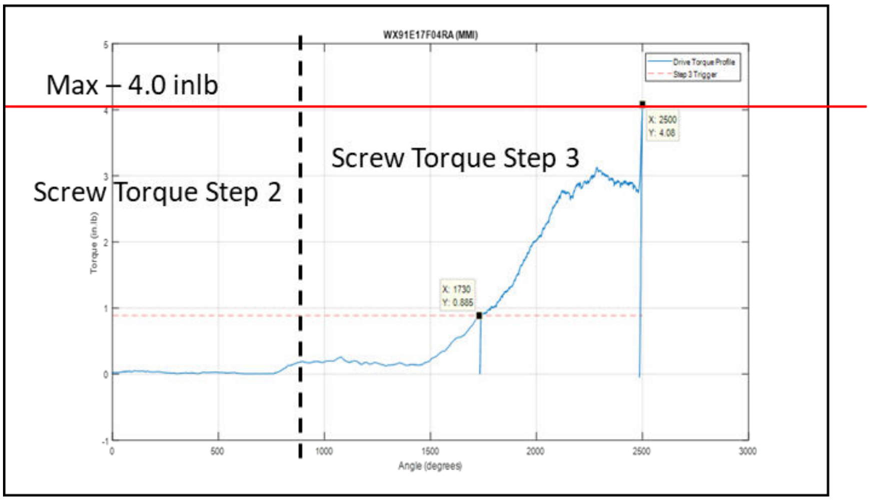

Figure-7. Torque profile on auto gang driver screw driving process.

DESIGN STUDY AND PROCEDURE

The first phase of the study was to prepare the pre-process data. Data were collected from Auto Gang Driver module from the NEO automation line. Eighty-three Hard Disk Drive was processed through the module, and the screw driving data, torque, height and angle rotation readings were collected (see Table-1). The Hard Disk Drive sub-assembly work piece was inspected; screw height and torque were measure and compared with drive data serial number. Drives that failed inspection were classified as “Failed”, and passed inspection was classified as “Passed”. The classification of “Passed” and Failed” are recorded. These data are labelled as training data.

The second phase of the study is performed cross-validation test using the k-Fold method on the training data. Five hundred data was collected from Auto Gang Driver and classified to use as training data. The cross-validation on the training data was performed on machine learning model for Support Vector and Decision Tree model. The cross-validation result was to validate the test data in terms of accuracy and error. The cross-validation with k-Fold method is performed using Open-Source Weka Software.

The third and last phase of the study, test data was obtained, and accuracy result is compared between Support Vector and Decision Tree machine learning model. The Support Vector Model and Decision Tree is deployed on to the Auto Gang Driver module. Forty-three sub-assembly drives were tested with Support Vector and Decision Tree model in the module, to compare the accuracy of detection. Two hundred and sixty data were generated, and were classified as “Passed” and “Failed”. Inspection and measurement of screw height and torque were measured. The inspection result is compared to the machine learning model output of both Support Vector and Decision Tree to calculate the accuracy. Result and analysis are further discussed in the following section.

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Table-1. Sample of process parameters and sensors.

Screw No	Screw Torque_Step 2	Screw Height	Screw Torque Step 3	Screw Total Angle
1	0.053	0.11	3.341	2623.594
2	0.039	0.128	3.447	2544.375
3	0.057	0.146	3.217	2544.375
4	0.053	0.128	3.46	2622.656
5	0.039	0.11	3.588	2772.656
6	0.017	0.108	3.659	2537.813

Screw Driving Classification Method

In this study, the focus is on screw driving process. The screw driving process can be broken down into for following steps:

a) **Pre-rotate screw:** The driver will pre-rotate screw in the air prior to engage to the work piece screw threaded hole. The purpose of pre-rotating the screw is to have the initial thread of the male thread to engage with female thread of the threaded hole on the work piece. Typically, the screw rotation speed is up to 500 rpm for it to successfully contact the first threaded hole.

b) **Screw torque step 2 process:** After the screw engages to the threaded hole, it continues to travel down, as it continues to rotate, the torque transducer on the driver is stable and near-zero if there are no friction between the screw thread and threaded hole on the work piece.

c) **Screw torque step 3 process:** As the screw continues to reach to the bottom, the transducer on the driver continues to increase the torque. This process happens in milliseconds. The dynamic torque data can be seen on the torque profile on the chart in Figure-6 below.

d) **Final torque:** Once the screw reached bottom, the torque continues to increase until screw stop. The driver will continue to rotate until the transducer reach it intended product torque specification. The torque maximum specification is 4.0inlb.

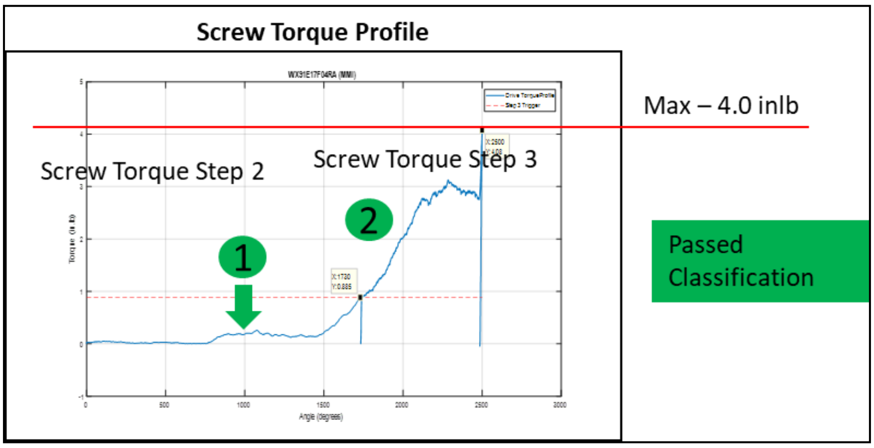

Figure-8. Torque Profile with Passed Classification.

If the screw driving process is labeled as “passed’ when it managed to complete all the process stated 1-4 above, and the torque profile is illustrated in Figure-8. It will be labeled as “failed”, if the process reaches the final torque, but the screw did not reach bottom. This happens if the screw is cross threaded against the threaded hole on the work piece, where it reaches the final torque and the screw appear physically high. The Failed screw driving process torque profile pattern is shown in Figure-9.

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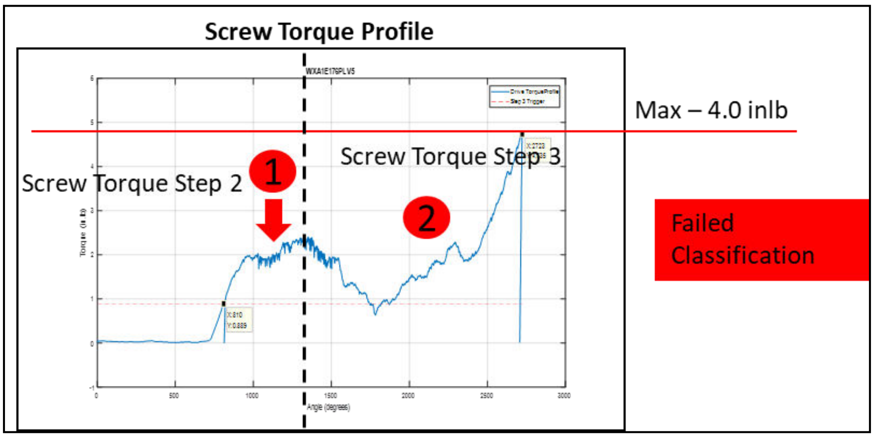

Figure-9. Torque profile with failed classification.

As shown in Figure-10, the Screw Torque Step 2 torque profile is high as the screw rotate and travels down. The dynamic torque signal is high because the screw encounters friction while threading downward, and higher torque is required to overcome the friction. However, if the screw unable to overcome the friction, the screw driving process will stop, and the screw will physically appear high on the work piece.

For this thesis experiment, the driver transducer will measure the screw torque for Screw Torque Step 2 and Step 3. Once, the driver reaches the torque requirement, the encoder sensor on the driver will measure the height of the screw and compared to specification.

RESULTS AND DISCUSSIONS

Cross-validation is performed on the training data set using the Support Vector model and Decision Tree Model. Cross validation is a re-sampling procedure commonly used to evaluate machine-learning model based on limited sampling data. Cross-validation using the k-Fold method is used to assess the skill on a machine-learning model based on unseen data. It is typical to generally assess how the machine-learning model is expected to perform prior to training the data. It provides an unbiased performance of the model skills. Configuration of k is equal to 10; this means that the 500-training data set are randomly shuffled 10 times.

Table-2 and Table-3 show the result for accuracy and confusion matrix for both models, respectively. Using k-fold cross validation, Support Vector Model training data set has prediction error of 0.1. This means that there is a 10% probability that the model will incorrectly predict the output of the model. The probability of the model correctly predicts the output of the model is 90%. For the Decision Tree Model has zero probability meaning that the model will incorrectly predict the output of the model. The probability of the model correctly predicts the output of the model is 100%.

Table-2. Results of k-fold cross validation.

Model	Accuracy	Precision
Support Vector Model	90%	89.6%
Decision Tree Model	100%	100%

Table-3. Confusion Matrix for (a) Support Vector Model, (b) Decision Tree Model.

Machine Learning Model	Support Vector Model			Decision Tree Model			
	a	b	Classification		a	b	Classification
a	381	16	Pass	a	397	0	Pass
b	34	69	Fail	b	0	103	Fail

Table-4. Result using test data set.

Machine Learning Model	Support Vector Model	Decision Tree Model
Correct Classification	249	260
Incorrect Classification	11	0
Accuracy	95.8%	100%

The 260-test data are input into the Support Vector Model in Machine Learning using Weka Software. Out of the 260 data, 249 data are correctly predicted by the model. The validation of the data was performed using

Visual and Mechanical Inspection criteria. The Support Vector model has incorrectly classified for 11 data; hence the accuracy is 95.8%. Decision Tree model has performed better with 100% accuracy as shown in Table-4.

CONCLUSIONS

Screw driving process relies on two key parameters to achieve successful process, achieve screw torque specification and screw height. If either one of these process fails, the process is not successful. In Support Vector model, the accuracy of the predictive is 95.8% with mean absolute error of 10%. The reason for the prediction error of 10% is because Support Vector Model is dependent on numerical and the standard deviation of the screw height and torque data. The model will classify the data into two group, and analyse the distance between two classify. The model will then predict the output of the model using the deviation between both groups and classify the data into “passed” and “failed”. It is because of the numerical nature of the model, there is 10% error in the prediction.

Decision Tree model prediction is 100%, as the model able to analyse and clear distinction between two classification. Therefore, the classification of the “passed” and failed” is the distinctive for the model to have 100% accuracy in its prediction output.

Machine learning can be used to create model based on the data set and classification and create a mathematical model and use the model to detect failure. A process control or health monitoring of the machine can be deployed to monitor and predict where the machines are due for maintenance. Engineers can use the data to analyse and work to correct the tool setup or perform maintenance on the tool to bring the tool back to healthy level. This save engineers time to develop and search pattern in the data to implement process control on the Manufacturing Line. There wide list of Machine Learning model that can be used to train data set to further improve the accuracy.

This study is process-based data that monitor the screw driving process, control and monitor to make sure that the process is in control, tool setup and machine specification are correct for a successful process. Future works can be explored to use machine learning to monitor and control incoming facilities and utilities. The air pressure monitoring data, robot speed, compressor air, sensor time delay data and so forth can be utilized and the machine learning model can support the predictive part to make sure that machine efficiency are 100% all the time.

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