Building The Health Monitoring and Fault Diagnosis Models For Stamping Press

Yuan-Jen Chang[1,2], Lin-Jie Chen[2], Yuta Tu[3], Hung-pin Yang[3], and Chen-Kang Lee[4]

[1] *Dept. of Aerospace and Systems Engineering, Feng Chia University, Taichung City, 407, Taiwan*
yjenchang@fcu.edu.tw

[2] *Master's Program of Data Science, Feng Chia University, Taichung City, 407, Taiwan*
a0980583939@gmail.com

[3] *Chin Fong Machine Industrial Co., Ltd, Changhua City, 500, Taiwan*
yuta2@chinfong.com.tw, besn@chinfong.com.tw

[4] *Department of Computer Science and Engineering, University of California San Diego, La Jolla, CA 92093, USA*
chl126@ucsd.edu

ABSTRACT

A stamping press is widely used for the metal forming process. To achieve continuous automation and high precision forming, monitoring the press's health and diagnosing faults during stamping is necessary. The three primary types of faults that may occur in the stamping press are lack of lubrication oil, quality variation of lubrication oil, and clearance variation, which can lead to a decline in workpiece quality and reduced lifespan of the dies and presses. This study adopted the Prognostics and Health Management (PHM) technique to implement a predictive maintenance system for the stamping press. To extract relevant data, the National Instrument (NI) DAQ was used to acquire the three-phase currents and X, Y, and Z vibration signals. Six signals provided a total of seventy-two features, and the top three key features were selected for building a health assessment model using the Logistic regression and PCA algorithms. An early warning is triggered when the health indicator drops below the threshold, alerting the operators. Additionally, fault diagnosis was achieved using classification algorithms such as Support Vector Machine (SVM), K Nearest Neighbors (K-NN), and eXtreme Gradient Boosting (XGBoost). The fault diagnosis model achieved high accuracies of up to 99%.

Keywords: Stamping press, Prognostics and Health Management (PHM), Health assessment, Fault diagnosis

1. INTRODUCTION

Smart manufacturing is a technique that uses interconnected devices, sensors, and software to create a more efficient and automated production process. On the production lines, many machine tools are used to process workpieces. A stamping press is a widely used machine tool to shape workpieces through processing. To enable a stamping press to perform continuous production, regular maintenance has become a necessary means of maintenance. The biggest problem with the maintenance of a stamping press lies in the lubricating oil. Insufficient lubrication or a decrease in the quality of the lubricating oil can lead to wear and tear on the punch-press mechanism. Inadequate lubrication can also cause the clearance to increase during the operation of the punch press and can lead to unplanned machine downtime, eventually resulting in additional production costs in the form of capacity loss, production loss, and direct labor costs for repairs (Lee et al., 2020). Additionally, the degradation of stamping presses may cause more burrs in the workpiece and a decrease in quality.

The use of technology has revolutionized the way manufacturing plants operate, and Prognostics and Health Management (PHM) is a vital component of this new approach. PHM refers to the process of monitoring the health of equipment and predicting when maintenance is required to prevent breakdowns. As a result, it helps manufacturing plants be more efficient, reduce costs, and increase productivity (Lee et al., 2020).

PHM allows manufacturers to reduce the risk of equipment failure and unplanned downtime. By detecting potential problems before they occur, manufacturers can schedule maintenance activities and avoid production interruptions. Incorporating PHM not only saves time and money but also increases safety by preventing accidents caused by equipment failure.

In addition to preventing breakdowns, PHM can help manufacturers optimize their operations. By analyzing data collected from sensors and other sources, manufacturers can identify patterns and trends and adjust their processes to improve efficiency and productivity. This can result in higher production, reduced waste, and higher-quality products.

In the current study, PHM was used to build a health monitoring model and a fault detection model to prevent unplanned breakdown of the stamping press. In addition, by monitoring the health of the stamping press and performing predictive maintenance, manufacturers can prolong the life of the machine and reduce the need for costly replacements.

2. Experimental Studies and Methodology

2.1. Design of experiments

This study aims to establish an intelligent predictive maintenance system for a single-point direct drive servo press (Chin Fong Machine Industrial Co., Ltd, 2023), as shown in Figure 1.

In the first experiment, we investigated three fault conditions: fault type 1: lack of lubricating oil; fault type 2: deterioration of the lubricating oil; and fault type 3: clearance variation. Four different levels of lubrication oil amount (A1: 60 CT/min, A2: 80 CT/min, A3: 95 CT/min, and A4: 115 CT/min), four different levels of lubrication oil quality (Q1: Normal, Q2: Mildly degraded, Q3: Medium degraded, and Q4: Severe degraded), and three different levels of clearance (C1: 0.3±0.05 mm, C2: 0.6±0.05 mm, C3: 0.8±0.05 mm) were provided by Chin Fong as listed in Table 1.

The second experiment is designed to investigate the degradation process of the stamping press. A continuous punching process without workpiece was performed for 48 days, except that 4 days shot down. The stamping press is kept running at 60 strokes per minute (SPM) constantly for 24 hours a day and 7 days a week. This experiment is intended to simulate the degradation of the stamping machine.

Figure 1. A single-point direct drive servo press (Chin Fong Machine Industrial Co., Ltd, 2023)

Table 1. The experimental parameters

Fault type 1	Fault type 2	Fault type 3
Amount of lubrication oil (CT/min)	Quality of lubrication oil	Clearance (mm)
(A1) 60	(Q1) Normal	(C1) 0.3±0.05
(A2) 80	(Q2) Mildly degraded	(C2) 0.6±0.05
(A3) 95	(Q3) Medium degraded	(C3) 0.8±0.05
(A4) 115	(Q4) Severe degraded	

2.2. The proposed methodology

The methodology proposed for this study is shown in the following steps (Li et al., 2018). The following steps include signal acquisition, data pre-processing, feature extraction/selection, and modeling.

2.2.1. Data acquisition

A current transformer (CTL-16-CLS, MISUMI Corporation) and a three-axis accelerometer (Model 356B11 - PCB Piezotronics, Inc.) are used to measure the current and press vibration under various working conditions. The signals measured by the current transformer and acceleration were then obtained by the data acquisition system (NI-9234 and NI-9215, National Instruments Corp.) and then transferred to a computer to save as files. The sampling rate is 10 KHz.

2.2.2. Data pre-process

Figure 2 shows the vibration signal for a complete interval of each punching cycle. Each punching interval was 1.2 seconds, comprising three parts: the impact moment, the slider moving upward, and the slider moving downward. Data were collected for more than 90 minutes. The three parts of the data were segmented and analyzed separately.

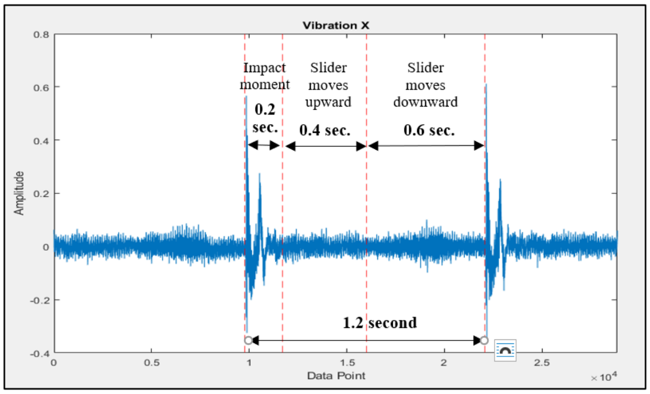


Figure 2. The vibration signal for a complete interval of each punching cycle.

2.2.3. Feature extraction/selection

The feature extraction was then performed in the time domain for each signal. For the time domain features, such as root mean square (RMS), mean, variance, kurtosis, skewness, peak to peak, energy, entropy, crest factor, shape factor, clearance factor, and impulse factor, are computed.

To select the key features, Fisher's criterion was used as a criterion function and is defined as (Fukunaga, 2013):

$$J_{f_l}(i,m) = \frac{\left|\mu_{i,f_l} - \mu_{m,f_l}\right|^2}{\sigma^2_{i,f_l} + \sigma^2_{m,f_l}} \qquad (1)$$

where μ_{i,f_l} and μ_{m,f_l} are the mean values of the lth feature, f_l, for classes i and m, respectively, and σ^2_{i,f_l} and σ^2_{m,f_l} are the variances of the l^{th} feature, f_l, for classes i and m, respectively. The feature subset can be selected from the available features with larger values of the function of the criterion using Fisher's criterion.

2.2.4. Modeling

For fault diagnosis, we adopted the Support Vector Machine (SVM), K-nearest Neighbor (KNN), and eXtreme Gradient Boosting (XGBoost) algorithm to establish a fault diagnosis model. The SVM algorithm (Hearst et al., 1998) is a machine learning model based on statistical learning theory. It has relative advantages in dealing with small-sample, nonlinear, high-dimensional, and local minimum problems. The KNN algorithm (Cunningham, 2021) is more straightforward. The classification is achieved by identifying the nearest k neighbors to a query sample and using those neighbors to determine the class of the query. The XGBoost algorithm is an improved algorithm based on the GBDT (Gradient Boosting Decision Tree) with the advantages of both Bagging and Boosting (Chen et al., 2020). Its advantage is that it can combine weak classifiers into a strong classifier, which is very helpful for building different fault diagnosis models for our electron beam evaporation equipment. Compared to SVM, it is more effective in handling complex combinations of fault labels.

In the second experiment, the Principal Component Analysis (PCA) technique (Thieullen et al., 2013) was adopted to calculate the health indicator using the Hotelling's T^2 value. The Hotelling's T^2 value is defined as follows.

$$T^2 = \left(\underline{x} - \mu\right)^T \Sigma_{\underline{X}}^{-1} \left(\underline{x} - \mu\right) \qquad (2)$$

Where Σ is sample covariance matrix, $\underline{x}$ is the mean of sample data, and μ is the mean of projected data. The Hotelling's T^2 value is proportional to the distance between the mean of sample data and the mean of projected data.

3. Results and Discussions

3.1. Classification model for detecting fault types

Traditionally, when abnormalities occur on a stamping press machine, it heavily relies on equipment maintenance engineers to come on-site to investigate what kind of malfunctions have occurred in order to carry out repairs. However, with our stamping press machine fault classification model, we can immediately identify what malfunction has occurred and carry out repairs without delay, thus reducing maintenance downtime.

For fault type diagnosis, we adopted SVM combined with PCA feature reduction to build a fault type classification model, as shown in Figure 3. Three types of faults, including 11 working conditions, neatly formed 3 groups. Each group indicated one fault type and the accuracy of fault classification was 100 %.

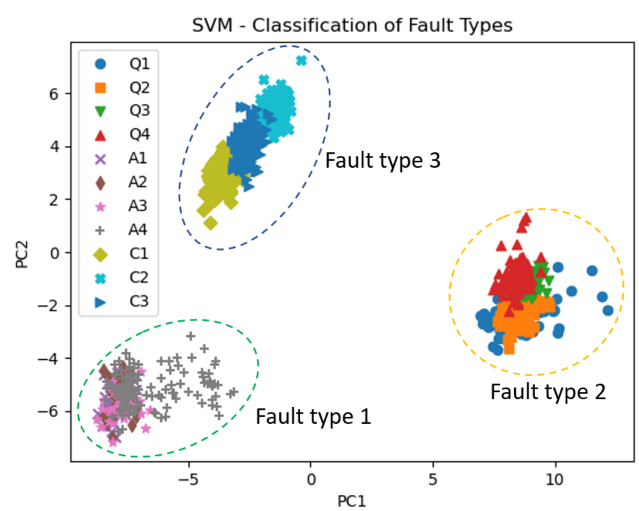
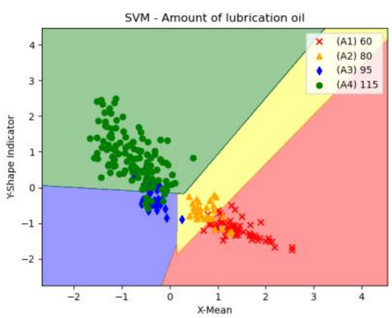


Figure 3. Classification model for various fault types.

3.2. Classification model for various amounts of lubrication oil

After determining the type of fault, we can further classify what causes it. For fault type 1, we would like to detect the amount of lubrication oil. Here, we adopted Fisher's criterion to choose the two most important features: the mean vibration X and shape indicator of vibration Y. We adopted three classification algorithms: SVM, XGBoost, and KNN on the features selected with Fisher's criterion to build the final classification model.

As shown in Figure 4, we use the two most important features, that is, the mean vibration X and the shape indicator of vibration Y, to plot the scatter plot. The accuracy of the SVM, XGBoost, and KNN models is 89%, 86%, and 87%, respectively. Although the accuracies on predicting individual conditions are not high, if we group working conditions into group of 60 and 80 CT/min, and the group of 95 and 115 CT/min, the model can achieve a much higher accuracy of 99.62%. It indicates that we can alert if the amount of lubrication oil is less than 80 CT/min, and notify the equipment maintenance engineers to add lubricating oil.



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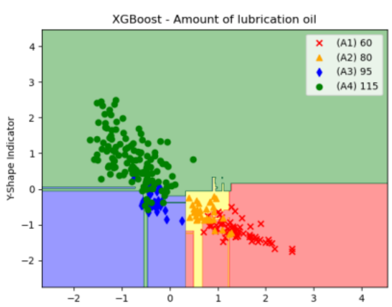

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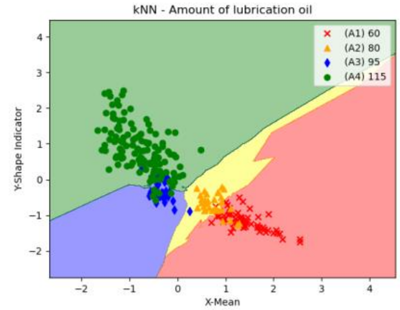

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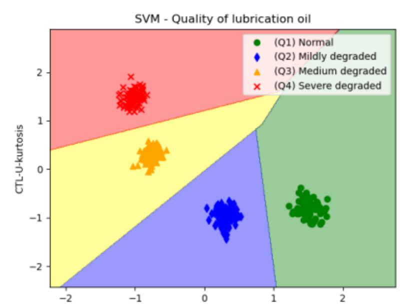
Figure 4. Classification model for various amounts of lubrication oil using (a) SVM; (b) XGBoost; and (c) KNN algorithm.

3.3. Classification model for detecting the quality of lubrication oil

For fault type 2, we would like to detect the quality of lubrication oil. We chose the Skewness of current V and the kurtosis of current U as the two most important feature by Fisher's criterion. Again, we adopted the three algorithms: SVM, XGBoost, and KNN, to build the classification model. As shown in Figure 5, we use the skewness of current V and the kurtosis of current U to plot the scatter plot. The accuracy of the SVM, XGBoost, and KNN models were all 100%. We can separate 4 quality levels of lubrication oil without any mixed samples. In other words, it indicates that we can determine if the quality of lubrication oil becomes mildly degraded or medium degraded from the feature we selected and notify the equipment maintenance engineers to replace the lubricating oil.



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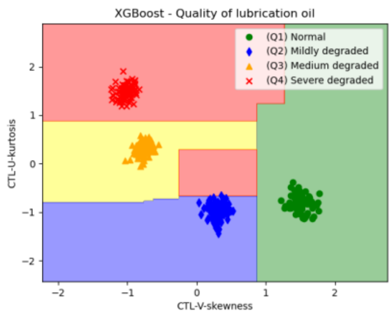

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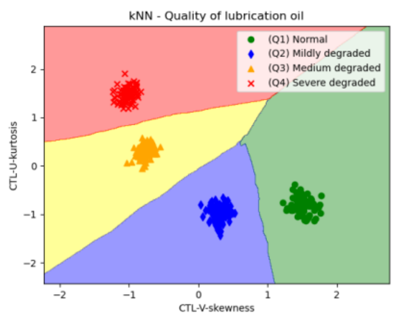

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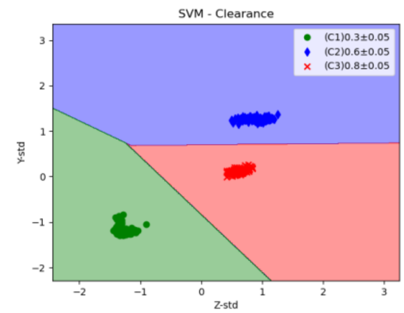
Figure 5. Classification model for detecting the quality of lubrication oil using (a) SVM; (b) XGBoost; and (c) KNN algorithm.

3.4. Model for detecting the clearance variation of stamping press

For fault type 3, we would like to detect the clearance variation. If the clearance of the stamping press increases, it may cause a decrease in the quality of the workpiece. Early warning can prevent the production of many scrapped workpieces. Therefore, we adopted Fisher's criterion to choose the two most important features, that is, the standard deviation of vibration Z and the standard deviation of vibration Y. Following the same procedure mentioned above, we adopted three classification algorithms, that is, SVM, XGBoost, and KNN combined with Fisher's criterion to build the classification model.

As shown in Figure 6, we use the two most important features, that is, the standard deviation of the vibration Z and the standard deviation of the vibration Y, to plot the scatter plot. The accuracy of the SVM, XGBoost and KNN models is 100%, 100%, and 100%, respectively. Of course, we can separate the three clearance levels without mixing samples. This indicates that if the height is greater than 0.6 or 0.8 mm, we can notify the equipment maintenance engineers and adjust the height.



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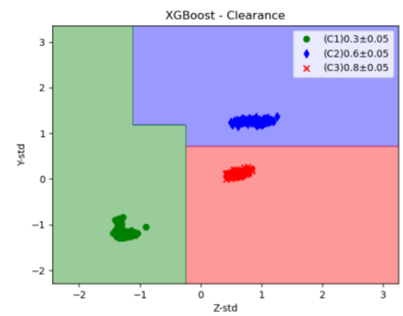

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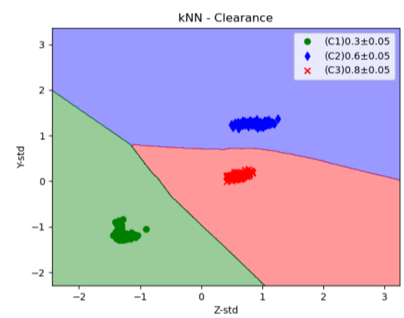

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Figure 6. Classification model for detecting the clearance variation using (a) SVM; (b) XGBoost; and (c) KNN algorithm.

3.5. Model evaluation

Based on the results of classification models, we can evaluate the performance of three fault type models. As shown in Table 2, the classification model to detect the quality of lubrication oil and the clearance is excellent. Although the accuracy of detecting the amount of lubrication oil is not high, we can issue an alarm if the amount of lubrication oil is less than 80 CT/min. In addition, the most important features for detecting the amount of lubrication oil and the clearance are vibration signals. It indicates that a lack of lubrication oil and clearance variation would cause severe vibration. However, the deterioration of the lubrication oil would cause the resistance force of the slider to vary. Thus, the current of the motor changes.

Table 2. The accuracy of classification model

Fault type Model	Amount of lubrication oil (CT/min)	Quality of lubrication oil	clearance (mm)
SVM algorithm	89.02%	100.00%	100.00%
XGBoost algorithm	86.25%	99.72%	100.00%
KNN algorithm	86.72%	100.00%	100.00%

3.6. Model for anomaly detection of stamping press

To monitor the health status, we adopted the Principal Component Analysis (PCA) technique to calculate the health indicator using the Hotelling's T^2 value. As shown in Figure 7, the health indicator was calculated for 48 days. A threshold for anomaly detection is established using the type 2 error alpha = 0.01. If the Hotelling's T^2 value is greater than the threshold value, it indicated the health status of the stamping machine is different significantly to original status. That is, the status of stamping machine is not healthy when the Hotelling's T^2 value is greater than the threshold value. Then, we have to use the classification models mentioned above to understand what kind of fault it is. Thus, equipment maintenance engineers can fix the machine accordingly. During the experiment, the Hotelling's T^2 values increased gradually at the 20th day. We found that all the Hotelling's T^2 values were greater than the threshold value from 26th day to 32th day, as shown in Figure 7. So the stamping press was shot down for two days from 33th day to 34th day. The maintenance engineer was called to fix the stamping press, including refilling the lubrication oil and adjusting the clearance. After restarting the stamping press, the Hotelling's T^2 values decreased gradually and become less than the threshold value at 42th day.

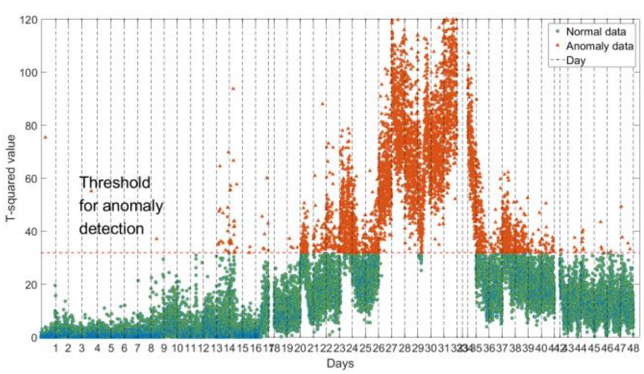

Figure 7. Anomaly detection model for stamping press

3.7. Discussions

In the current study, we conducted the experiment without using workpieces during stamping process. The result will not change if workpieces are used during the stamping process. Because the signals measured are vibration signals and current signals in the period of crank upwards and downward. The moment of impact when the workpieces are punched will not affect the measurement.

In addition, the model built in the current study can easily be extended to other similar type of stamping press. The effect of individual differences is only the baseline variation of each stamping press because the stamping press is a machine assembled with many different components. We can take few measurements to determine the baseline before applying the current model to other similar type of stamping press machines.

4. Conclusion

In this study, we built a classification model with support vector machine algorithm and principal component analysis to detect the type of fault. Then, three classification models with features selected from Fisher's criterion were built to further detect the level for each fault type. Finally, an anomaly detection model was built. Together these models help equipment maintenance engineers monitor the health status. When an anomaly is detected, one can immediately understand what kind of fault it is by using the classification model. Models can reduce the effort of equipment maintenance engineers. Furthermore, models can help equipment maintenance engineers carry out repairs without delay, thus reducing maintenance downtime. On top of that, maintaining the stamping press in healthy condition would avoid the production of scrapped workpieces and thus reduce the extra cost.

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