# Machine Learning-Based Methods For In-Time Monitoring Equipment Conditions.

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**Abstract**

**Traditionally, in semiconductor wafer manufacturing, the discovery of equipment abnormality has completely relied on the production engineers to check equipment parameter trend charts or individual values. However, some changes are very settle and not easily detected, some abnormalities are confounded in a complex state, and some abnormalities cannot be discovered at all. To overcome the drawbacks of manual detection, this paper describes our approach of using multiple machine learning methods to train models with production equipment data for assisting production engineers to comprehensively monitor equipment conditions in real-time.**

**We use Decision Tree, Random Forest, AdaBoost, SVM and other machine learning algorithms to establish classification models. For verifying the performance of models, we calculate the accuracy and AUC (Area Under Curve) metrics, and choose the best method accordingly. We use the best model to further explore the root cause of abnormality for a given equipment. Eventually, we can indeed capture the abnormal condition of the equipment in real-time.**

## INTRODUCTION

Maintenance cost is a major share of the total operating cost of all production or utilities of a manufacturing plant. Establishing an effective and efficient maintenance process will help the company to reduce costs. Maintenance can be divided into several levels, from the basic "reactive maintenance", "condition-based maintenance (CBM)" to the highest level "predictive maintenance (PdM)", Reactive maintenance means that equipment will be maintained or even replaced when it runs abnormal. Since settle equipment parameter changes are not easily detected, and some abnormalities cannot be discovered, most of the equipment engineers in manufacturing adopt reactive maintenance as the standard strategy. However, this method reduces production output and can impact quality considerably, causing high costs. Others adopt the CBM maintenance strategy, that is, the production engineers determines key equipment parameters or features based on experience, then set thresholds and monitor them. But abnormalities are not limited to certain key features and engineers cannot monitor them around the clock. Based on the above limitations, we are now using multiple machine learning methods to train classification models with recorded equipment data to monitor the equipment status.

The process difference between an engineer and a classification model is shown in Figure 1. Except for some imperceptible changes and subjective judgments, the biggest shortcoming of an engineer is that it cannot monitor the equipment around the clock and cannot detect abnormalities in real-time. On the other hand, model-based monitoring can not only detect minor changes and make objective and accurate judgments but also can monitor equipment around the clock. Once the model predicts that a result is abnormal, the engineer can be notified immediately to intervene. This methodology may prevent discrepant products being produced, as well as to allocate the production resources more effectively, which greatly improves the production efficiency.

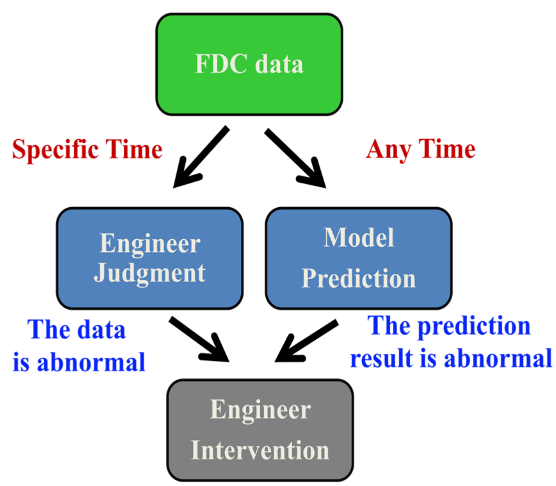


Fig. 1. The difference between engineers and model monitoring equipment process.

## BACKGROUND

Our equipment collects FDC (Fault Detection and Classification) data during wafer processing. In a subsequent process, the datasets are parsed into a database from where we can extract it through our EDA system. According to the data analysis and the engineer's judgment, FDC data are summarized in three cases as shown in Figure 2. In Case 1, a key feature or parameter is an indicator for normal or abnormal behavior of an equipment. In contrast to Case 1, key features in Case 2 are not sufficient by itself.

Case 3 indicates that key features indicating normal and abnormal behavior of the equipment cannot be identified. The data recorded by each equipment are about tens of thousands to hundreds of thousands of rows, and the number of features is about dozens, including time, temperature, pressure, flow, equipment status, and other equipment parameters. Some equipment processes two or three steps in a process flow, utilizing different chambers. Nevertheless, the recorded features are not all the same at different steps as shown in Figure 3. As an example, a features recorded is represented by the same character "A". However, even if the features are the same for each chamber, the values can be very different at the different steps.

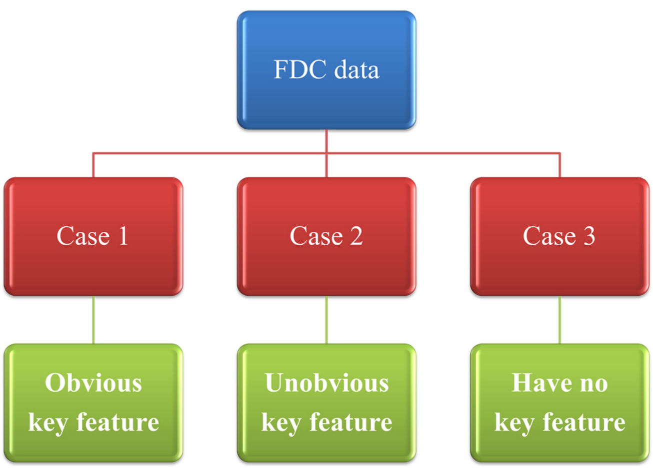


Fig. 2. There are three situations on FDC data

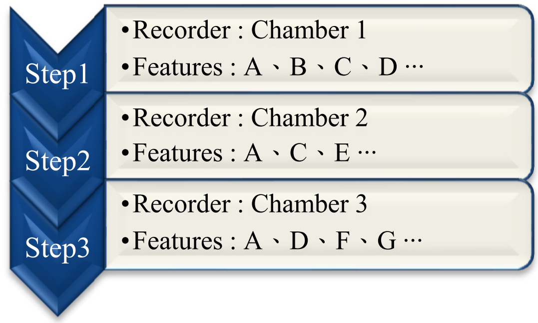


Fig.3. Examples of recording features on different chambers.

## EXPERIMENT

### *Data Preprocessing*

First, after extracting the dataset, we perform data preprocessing to delete unnecessary features, including those with the same value in all samples at wafer processing time. Next step is data cleaning to address missing values. There can be cases where data is lost. We use KNN (K = 10) to impute the missing values. The idea of the KNN method is to identify 'K' samples in the dataset that are similar or close in the features. Then we use these 'K' samples to estimate the value of a missing data points. Each missing value of a sample is imputed using the mean value of the 'K'- neighbors found in the dataset. Finally, categorical features are processed as many machine learning algorithms need their input features to be numeric. We don't have many categorical features in our datasets; thus, we use one-hot encoding to convert them. One-Hot encoding splits a category column into multiple columns, one for each unique category value. The values in each new column are set to 1 or 0 according to the values of the original category feature (1 meaning TRUE and 0 meaning FALSE).

### *Data Modeling*

We used Decision Trees [1], Random Forest [2], AdaBoost [3], SVM [4] and other algorithms to train classification models. The equipment status is our target variable. The value is 1 (normal) or 0 (abnormal). To test the performance of a model with "unseen" data, the data is randomly split between a training set (80%) and a test set (20%). In addition, to avoid single random sampling of the test set, which may unfortunately be sampled to extreme situations, we use the k-fold cross-validation (k = 5) method [5] as shown in Figure 4. It divides the data into five equal parts, one part into a test set and the other four parts into a training set. Each part will be evaluated with the test set. Therefore, five test results will be obtained. The accuracy and AUC of the five results of each model are averaged and compared, and the best method will be selected. AUC represents the area under a ROC curve (see Figure 5) and measures how well the model classifies between normal and abnormal cases. ROC in this case can be interpreted as visual confusion matrix.

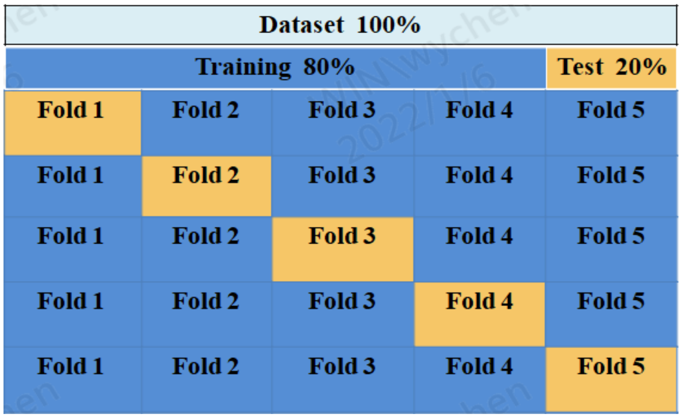


Fig. 4. Structure of five-fold cross-validation

*Feature Importance*

Each model used in this experiment can output or calculate feature importance. It ranks how important a feature or equipment parameter is in predicting a target variable. An example is shown in Figure 6. The best performing model of equipment LOF-10 is random forest. After calculation, we can get key features are pressure and flow. The important features obtained by the model will be compared to those provided by the production engineers. Except for Case 3, which has no key feature. The model identified all key features or equipment parameters provided by the production engineers.

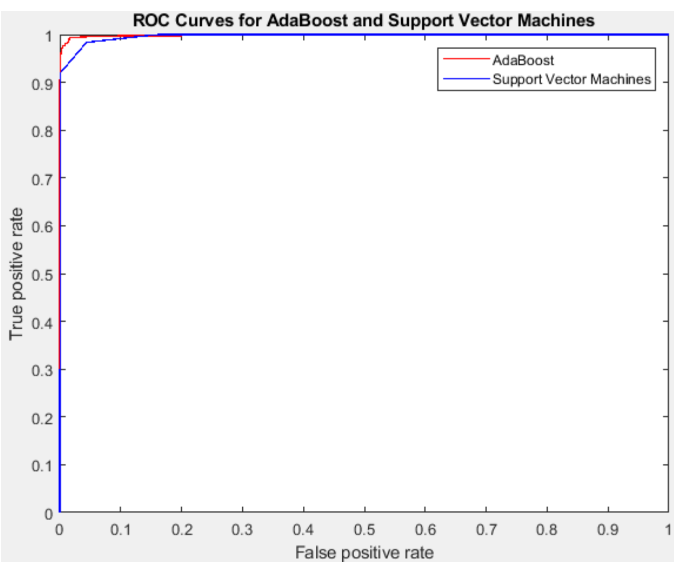


Fig. 5. Examples of ROC curves for AdaBoost and SVM.

This way, monitoring equipment can not only observe the results predicted by the model, but also observe whether the key feature values are abnormal at same time.

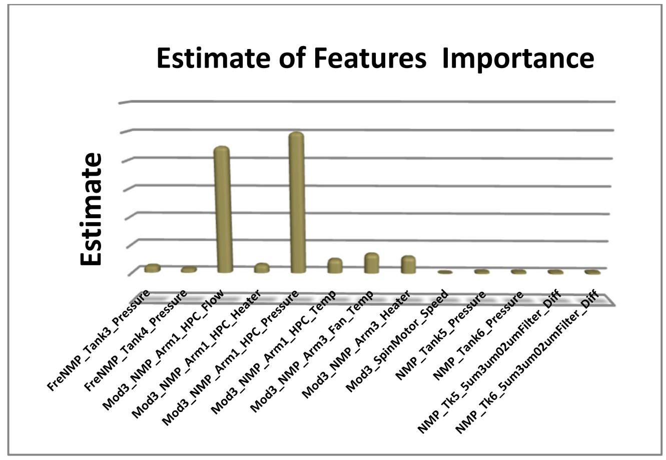


Fig. 6. Estimate of LOF-10 features importance

*Results*

Table I shows the accuracy of the prediction result. Accuracy of predicting whether the equipment is in normal or abnormal state is higher than 99%. To prevent the model from being affected by outliers, we defined that when the model predicts an abnormality three times in a row, it will pop up warning message, as shown in Figure 7. At the same time, we also check the line chart of the key feature as well, as shown in Figure 8. We found that the value of flow decreased slightly and we are sure that the equipment is abnormal. Therefore, the person in charge of the equipment can address of the abnormality.

TABLE I
EXAMPLES OF PREDICTION ACCURACY OF ALL EQUIPMENT

| Equipment | Accuracy | Key features |
|---|---|---|
| LOF-14 (Case1) | 99.9% | Temp |
| LOF-8 (Case2) | 99.5% | Flow |
| LOF-9 (Case2) | 99.9% | Flow |
| LOF-10 (Case2) | 99.9% | Pressure、Flow |
| PCD-7 (Case3) | 99.6% | Not exist |


Fig. 7. LOF-10 warning message

## CONCLUSIONS AND PROSPECT

So far models can indeed accurately predict the equipment abnormality in real-time. We also developed an automated system as shown in Figure 9. which will be deployed in the future.

This year we also expect to upgrade the maintenance level from CBM to PdM. Whenever you can diagnose the equipment error, you can schedule the maintenance ahead of time, to effectively manage inventory, to minimize the downtime, and to enhance the operational potency.

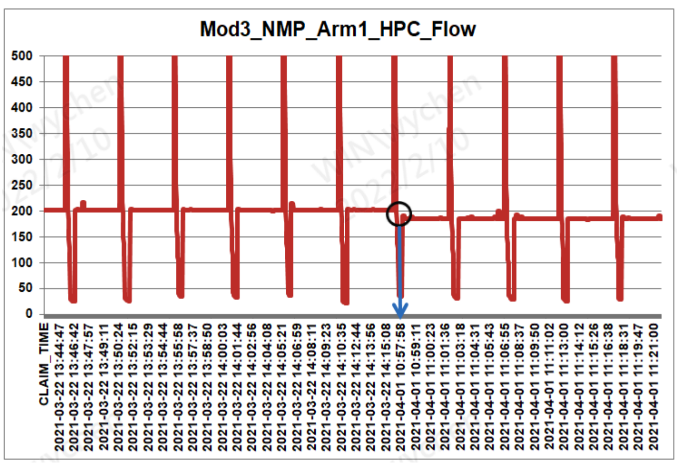


Fig. 8. LOF-10 line chart of Flow

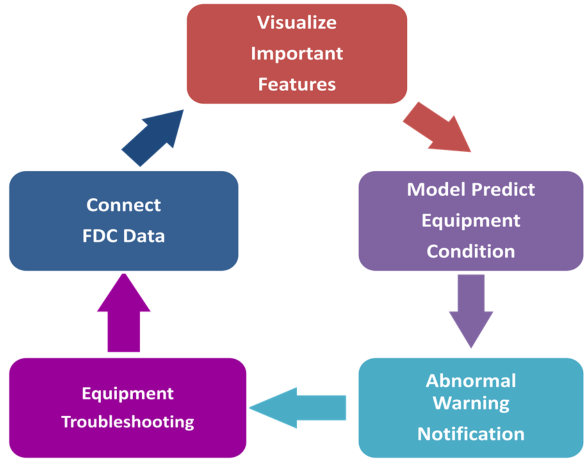


Fig. 9. Flowchart of the implementation system

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## ACRONYMS

CBM : Condition Based Maintenance
PdM : Predictive Maintenance
SVM : Support Vector Machine
EDA : Engineering Data Analysis System
KNN : K-Nearest Neighbor
ROC : Receiver Operating Characteristic Curve
AUC : Area under the ROC curve