Maintenance Time Reduction for Semiconductor Manufacturing Tools

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***Abstract*— This work develops a method to reduce the maintenance time for semiconductor manufacturing tools used for the atomic layer deposition (ALD) process. ALD tools conduct a periodic maintenance operation, which consists of cleaning and pre-conditioning steps, to eliminate impurities attached inside the chamber wall. This work proposes an algorithm to detect the appropriate completion time of the cleaning and pre-conditioning steps and applies it with real ALD data.**

Keywords: Semiconductor manufacturing equipment, Maintenance, Cleaning, Pre-conditioning, Machine learning

I. INTRODUCTION

Semiconductor manufacturing tools, especially used for atomic layer deposition (ALD), periodically conduct maintenance operations. The maintenance operation mainly consists of cleaning and pre-conditioning steps and takes about a day. All of impurities are removed in the cleaning step, and the pre-conditioning step makes the tool state ready to process a new wafer. It is hard to detect the accurate completion time of the cleaning or pre-conditioning process, and tool engineers tend to run more recipes for such a maintenance operation to be safe. Therefore, it is required to detect the appropriate completion time to avoid excessive maintenance operations. However, there is no dependent variable in the data which indicates the exact completion time, and only the reference data where the corresponding maintenance process is completed appropriately. Hence, it is required to use the unsupervised learning method for the problem, and we propose a cluster centroid distance-based approach with the real ALD data.

II. SOLUTION APPROACH

A. Feature selection method

First, a feature selection process is applied to the ALD data to extract important features that represent the tool state during the maintenance operation. We select some of important features first by using the domain knowledge from the tool engineers and then eliminate redundant features based on the location of sensors. We finally apply the dynamic time warping (DTW)-based clustering algorithm which measures the similarity between time-series sequences and makes groups with features having large similarities [1]. The features in the same group are removed except for one.

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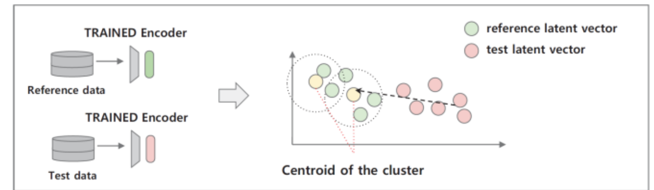

Figure 1. Cluster Centroid Distance-based approach.

B. Cluster Centroid Distance-based approach

We now propose a method that computes the distance between the given test data from the reference data. The data, both the test and reference data, are first transformed into the low dimensions with the LSTM-Autoencoder, and the latent vectors are used in computing the distance [2]. We train the LSTM-Autoencoder model with reference data, and the encoder of the model is designed as a non-linear mapping function. Then the centroids of the transformed reference data are obtained with the K-means clustering algorithm, and they are used in calculating the distance from the test data [3]. Fig. 1 shows the overall procedure of the proposed method.

III. EXPERIMENT

We conduct the experiment with the real ALD process data for both cleaning and pre-conditioning steps which consist of multiple cycles. Fig. 2 shows the distance from the reference data to the test data for cleaning and pre-conditioning steps, respectively. It is observed that the distance tends to decrease as it becomes close to the tool state of the reference data. It is then possible to set a threshold and stop the cleaning or pre-condition step when the distance is below the threshold.

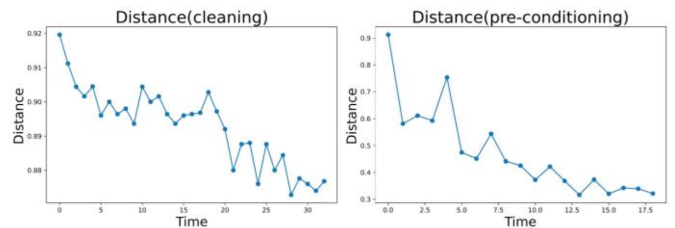

Figure 2. Distance between reference data and test data.

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