[Endpoint Prediction for ICP Etching Process with Smart VM Method- Junya Nishiguchi]

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Abstract:
In MEMS fabrications as a mechanical sensor, the accuracy of it requires precise control of the dimension which decides its characteristics. In this work, we examined a virtual metrology (VM) procedure that consists of anomaly data detection and Equipment Engineering System (EES). Proposed method is applied to estimation of the etching rate of ICP etching process for endpoint detection.

Background:
The etching depth is one of critical parameters in ICP etching process of the dielectric substrate for mechanical sensors, since it decides the basic characteristics of the sensors. It is however impossible to monitor the etching depth of single material etching process in situ with optical emission changes. In this case, it is effective to estimate etching rate with VM model during production. The etching rate forecasts the time to reach the endpoint (i.e. targeted etching depth) prior to finish the process as shown in figure 1. The VM model needs to be sequentially updated for utilizing limited data in high-mix low volume production. Also, the data to be adopted in the VM model should be examined so as not to degrade the estimation performance.

Approaches:
The procedure of this work is shown in figure 2. It consists of three steps as follows.

1. Anomaly data detection

We apply Multivariate Time-series Shape Analysis (MTSA[1]) for anomaly detection. MTSA watches the shape of the time series data and detects anomaly data automatically even when the length of the time varies wafer to wafer in process as shown in figure 3.

2. Feature extraction

The EES[2] applied for VM model building summarizes time series data even when multi steps etching is carried out to get deep cavity to build a MEMS sensor. Typical summarization process is described in figure 4.

3. Sequential VM model building

The modeling process constructs the regression model representing the relationship between features and etching rate. The model is updated sequentially when new measured data is taken. Our method judges whether new data is adopted for the VM model by comparing the accuracy when adopting and not adopting anomaly data specified by MTSA.

Results and discussions:
This section shows the effectiveness of the proposed method with ICP etching process data. The data is obtained from 74 wafers with 29 process variables of tool data and each process takes several hours but different in length each other.
As shown in figure 5, the difference between normal and anomaly data with representative process variables. The figure shows MTSA detects anomaly data according to variance of the each process variable. The detected anomaly data actually reveal to be a symptom of the tool failure as shown in figure 6.
Then we apply multiple regressions as VM model for the extracted feature by EES such as an average or a standard deviation of each wafer's data.
The results of VM model accuracy when adopting and not adopting anomaly data are shown in figure 7 and figure 8, respectively. Note that each figure compares actual and estimated etching rate and scatter plot does not include anomaly data. These results represent the VM model accuracy improves with adopting anomaly data. This indicates that even detected anomaly data behaves correctly to explain the physics of the etching process. As a result, the VM model is accurate enough to estimate the etching rate for endpoint detection of the process.

Conclusions:
We have presented the way to build an effective VM model to improve the ICP etching accuracy to fabricate a MEMS sensor. MTSA which is a machine learning approach and a conventional EES can work complimentary and reduce human efforts and fluctuations with limited volume of data in high-mix low volume production.

References:
[1] T. Suzuki et al. “An Online Anomaly Detection System Supporting Batch-Process Operator Decision-Making” Apr. 2018 Azbil Technical Review
[2] T. Kurosawa et al. “Highly sensitive process condition monitoring method by using temporal data from production process” Mar. 2019 IEEJ

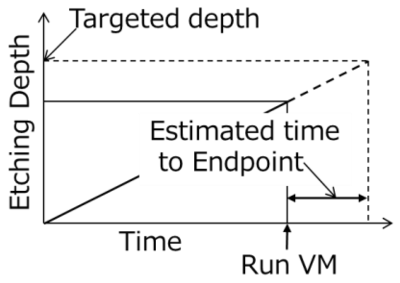

Figure 1. VM to estimate the additional etching time

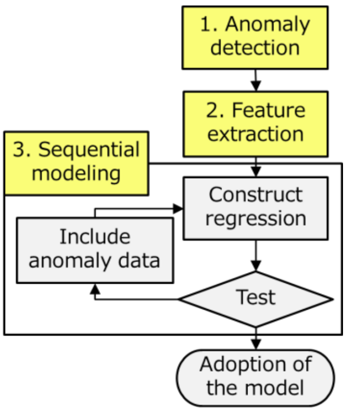

Figure 2. The procedure to build the VM model

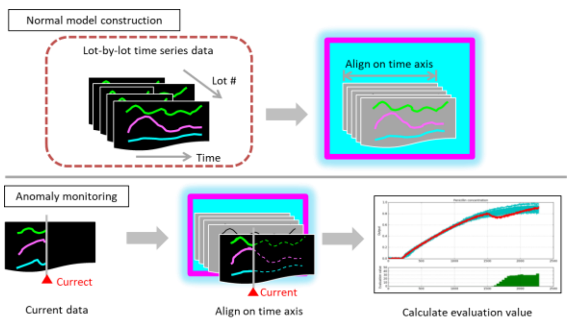

Figure 3. Overview of MTSA

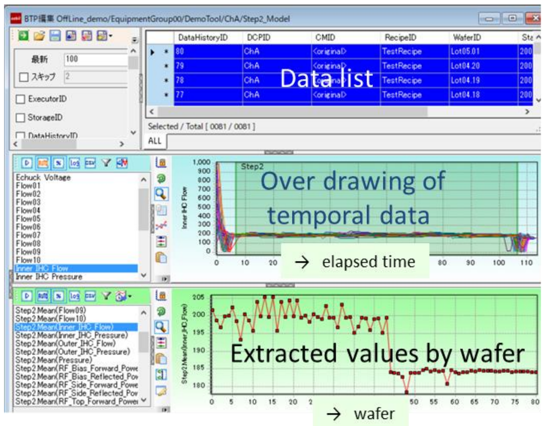

Figure 4. Summarization of temporal data by EES

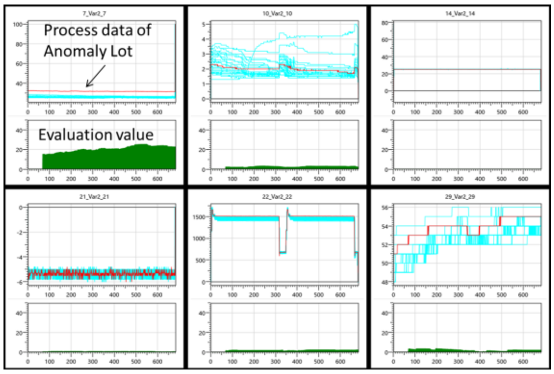

Figure 5. Result of anomaly detection

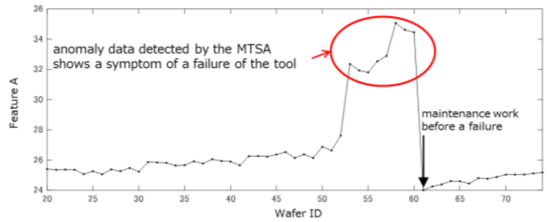

Figure 6. Anomaly data detected by MTSA shows a sympton of a failure of the tool

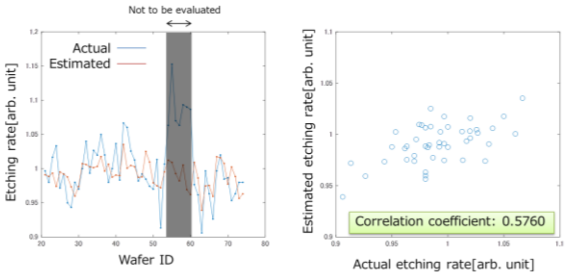

Figure 7. Result of VM model without anomaly data

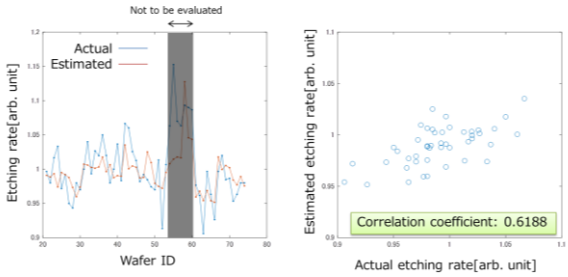

Figure 8. Result of VM model with anomaly data