Advanced FDC Method using EWMA – Yuko Jisaki

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1. Introduction

To improve overall equipment efficiency in semiconductor manufacturing, i.e., achieve higher yield and lower costs, a predictive maintenance (PdM) technique, is needed to be able to maintain equipment at the correct timing based on equipment sensor data. Constant monitoring of the entire volume of sensor data would ideal, but would be difficult to achieve with existing commercially-available systems, which are not designed for labor-saving purposes. This makes PdM based on a multivariate model of particular interest. However, there is little prospect of actually using multivariate-model PdM, since models of this type tend to be difficult to construct and maintain. To resolve this problem, we have developed a novel method of fault detection and classification (FDC) for our own fab-wide FDC system that can detect abnormities in a mass of sensor data, is accurate, and is easy to maintain [1]. This paper describes, as an example, the successful application of our new method using EWMA to copper electroplating.

2. Approach

The key to the efficient monitoring of sensors is the interpretation of each equipment sensor's output. All parameters can be divided into two categories through physical phenomenon in the process chamber: active parameters, which are set values imposed within the process recipe; and passive parameters, which change with the variations in physical phenomena in the process chamber. Certain physical phenomena determine the process results on the wafer, through a transfer function, as shown in Figure 1 [2], which should therefore be observed as changes in passive variables. To achieve the practical use of PdM, it is necessary to monitor each passive parameter at high sensitivity and to predict the process result on a wafer using a virtual metrology (VM) model which can be constructed based on these passive parameters. However, passive parameters may vary as the number of process wafers increases, and may change after chamber maintenance. Fixed control limits cannot detect faults at high sensitivity, and therefore require model maintenance. We devised the new method shown in Figure 2. Active parameters are monitored in conventional fashion by fixed control limits; however, passive parameters are monitored by means of variable control limits, and the baseline is calculated using an exponentially-weighted moving average (EWMA). The predicted process result using the VM model is monitored by fixed control limits as needed. To cope with the changing patterns of passive variables caused by maintenance, we developed a function by which the variable control limit can be reset automatically when the system receives the maintenance information signal, as shown in Figure 3. The new EWMA function was applied to copper plating equipment and was verified in comparison with a multivariate model using a practical test.

3. Results

Figure 4 is a schematic drawing of the copper electroplating equipment. It comprises an anode and a cathode submerged in a plating cell filled with a plating bath. The copper film is formed when voltage is applied to the electrodes at constant current. As the integral of the current consumption increases, the thickness of the anode decreases. The plating voltage rises with increasing distance between the two electrodes. Figure 5 shows the anode voltage during copper electroplating. As can be seen, the excursions, which indicate abnormalities, cannot be detected by a fixed control limit but can be detected by a variable control limit. The excursions were caused by electrolytic slime in the plating bath and were eliminated by replacing the filter in the circulation line. Figure 6 shows the result of applying sensing capability in a multivariate statistical process control model based on principal component analysis (PCA-MSPC) using all the collected parameters. As shown Figure 6, Hotelling's T^2 statistics and Q statistics are both difficult to detect and show false-positive excursions, possibly because the figures are comprised of statistically compressed data.

4. Summary

We have developed a new FDC method using EWMA in our existing fab-wide FDC system. It can detect abnormities in passive parameters, which tend to be difficult to monitor, with high sensitivity. Our total FDC setup, including the new method for all tools, achieved a 90% reduction in the incidence of electrically faulty wafers.

References
[1] T. Tsuda *et al.*, ISSM2014 (2014)
[2] S. Imai, ISSM2008 (2008)

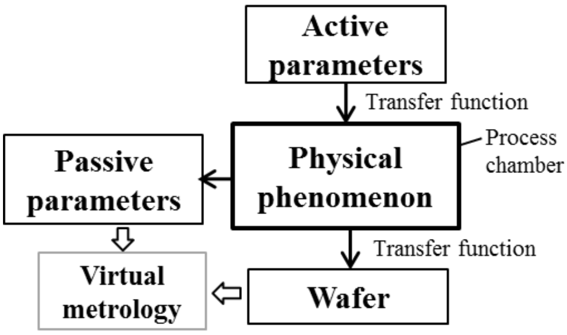

Figure 1. Diagram of the relationship between equipment parameters. All parameters can be classified as either active parameters or passive parameters.

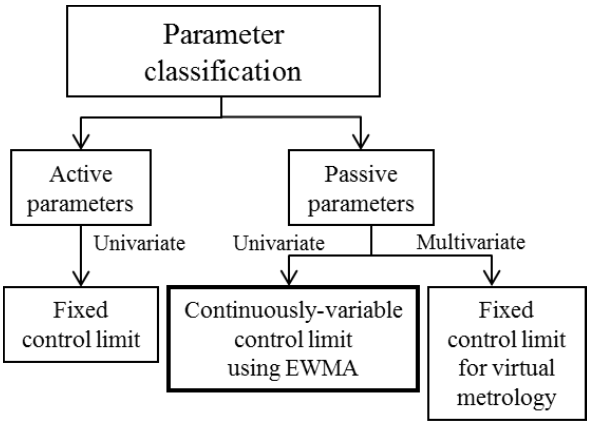

Figure 2. Flowchart of FDC setup based on the parameter classification.

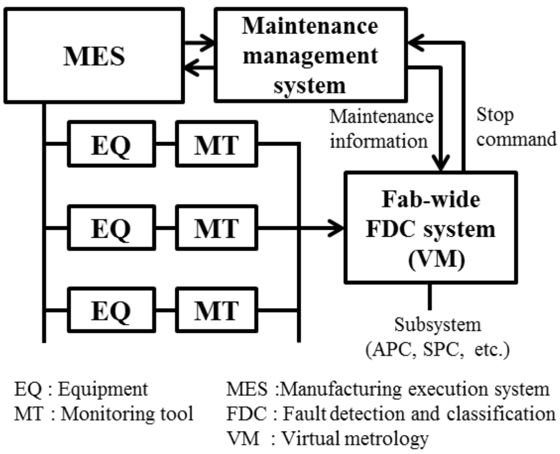

Figure 3. Schematic drawing of fab-wide FDC system that is linked to equipment maintenance information.

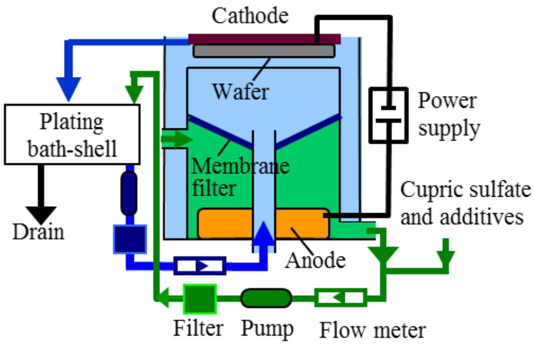

Figure 4. Schematic drawing of copper electroplating equipment.

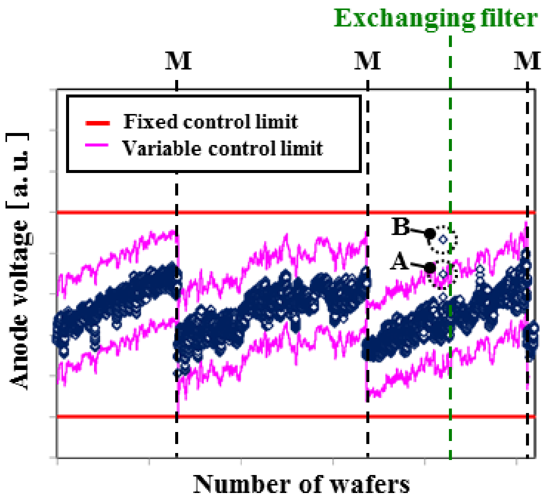

Figure 5. Chart showing anode voltage of copper electroplating equipment. "M" in the Figure indicates maintenance. A and B are abnormities that should be detected.

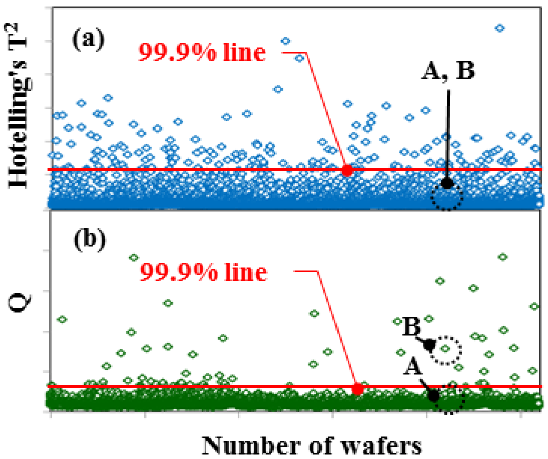

Figure 6. Statistical quantities using the PCA-MSPC model for copper electroplating equipment. A and B are abnormities which need to be detected. (a) Hotelling's T^2, (b) Q.