

## Prediction in gate oxide thickness using virtual metrology technology

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### 1. Introduction

The progress of miniaturization in a semiconductor device leads to narrow a device margin. The tendency becomes remarkable in a nanometer device. Since equipment fluctuation has not fallen within a device margin, it is a serious problem in manufacturing<sup>1)</sup>. To elude yield degradation due to equipment fluctuation, practical applications of equipment monitoring using EES and process control have been significant. In particular, since process control using equipment variables is crucial, advanced process control (APC) and fault detection and classification (FDC) using virtual metrology (VM) are notable. We reported fab-wide FDC and VM-FDC applications in this symposium and other meeting<sup>2)-4)</sup>. This paper describes the VM technology in gate-oxide ( $G_{ox}$ ) formation, which is the most important process in semiconductor manufacturing.

### 2. Experiment

#### 2.1 Equipment for gate-oxide film

Figure 1 shows schematic drawing of a chamber in rapid thermal processing (RTP) for  $G_{ox}$  film. A lamp head with several halogen lamps is equipped at the upper portion in the chamber. Output power in lamps, which are arranged in 15 zones, is controlled by measuring wafer temperature ( $T_w$ ). RTP equipment has a  $T_w$  measurement system, which is composed of 7 pyrometers to measure  $T_w$  and an emissometer to obtain wafer emissivity at the backside of a wafer. As is common knowledge, since RTP usually has short process time, the sampling rate should be taken care in EES. In our monitoring system, the maximum sampling rate is 100 Hz<sup>5)</sup> and is enough to monitor  $T_w$ . The other monitoring variables are lamp output power  $I_i$  ( $i=1...15$ ), chamber pressure  $P$ , lamp head pressure  $p$ , gas flow rates and wafer emissivity  $\varepsilon$ .

#### 2.2 VM model for gate-oxide deposition rate

In making a VM model, a regression model is widely used. A regression model in a  $G_{ox}$  deposition rate using lamp output power  $I_i$  ( $i=1...15$ ) and chamber pressure  $P$  is represented as follows:

$$R = a_0 + \sum_{i=1}^{15} a_i I_i + a_{16} P. \quad (1)$$

Here,  $a_i$  ( $i=0...16$ ) is constant.

We have addressed that in developing a VM model, both approaches in a statistical analysis and physical model investigation are powerful<sup>3)</sup>. Then, following a statistical analysis for equipment variables, a physical model on a  $G_{ox}$  deposition rate is derived. Assuming that the deposition rate is proportional to oxygen

radical density and thermal energy, the VM model is represented as follows:

$$R = P \left\{ \sum_{i=1}^{15} a_i I_i - f(p, \varepsilon, I) \right\}. \quad (2)$$

Here,  $f(p, \varepsilon, I)$  is a kind of a loss function. By learning in both VM models represented by Eq. (1) and Eq. (2) using actual manufacturing data (i.e., equipment variables and  $G_{ox}$  deposition rates), coefficients in Eq. (1) and Eq. (2) were determined for a period. The model accuracies, which are defined as correlation factors, are compared between both VM models in learning. As a result, a VM model with higher accuracy is used to predict a  $G_{ox}$  deposition rate. Moreover, by using the VM model,  $G_{ox}$  thickness is predicted and the actual inspection in  $G_{ox}$  thickness is changed to a VM inspection.

### 3. Results and Discussion

In  $G_{ox}$  thickness difference between actual and target thicknesses, a correlation factor between measured and learned  $G_{ox}$  thicknesses in Eq. (1) was 0.72 (Fig. 2). On the other hand, as shown in Fig. 3, a correlation factor in Eq. (2) was up to 0.89. From these results, it was revealed that the VM model by Eq. (2) was better to predict  $G_{ox}$  thickness. Figure 4 shows predicted  $G_{ox}$  thickness (difference) in each manufacturing lot. The correlation factor was 0.92 in prediction and was kept to be high accuracy achieved in learning, resulting that VM-FDC was successfully performed. Note that after performing equipment maintenance, prediction accuracy is kept without relearning. By changing  $G_{ox}$  inspection using NPW to VM,  $G_{ox}$  quality control using NPW in each lot was eliminated. As a result, 2.2 % NPW for production wafers per month could be reduced.

Finally, we describe effective oxide thickness (EOT) in  $G_{ox}$  measured by an electric test with relationship of predicted thickness by our VM model. EOTs over measured and predicted thicknesses are shown in Figs 5(a) and (b). The predicted thickness by VM correlates strongly with EOT, comparing the measured thickness. Thus, VM does not only contribute to manufacturing cost reduction, but also is effective for enhancing product quality and yield.

### 4. Summary

We have developed a VM model for  $G_{ox}$  by incorporating a physical model into VM. The VM model can predict  $G_{ox}$  thickness. It was demonstrated that predicted  $G_{ox}$  thickness correlates with EOT. Through our VM activity, fruitful benefits in NPW reduction and FDC were brought in our factory.

**References**

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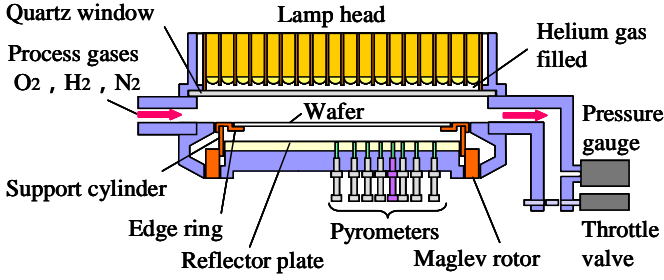


Fig. 1

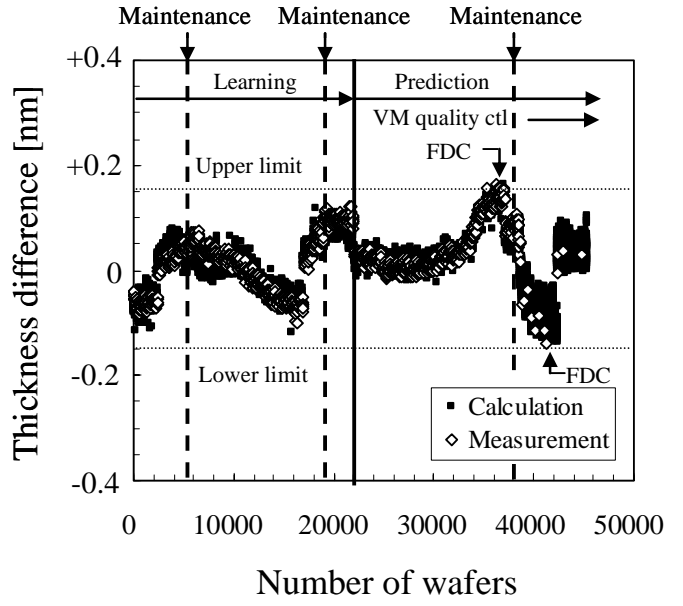


Fig. 4

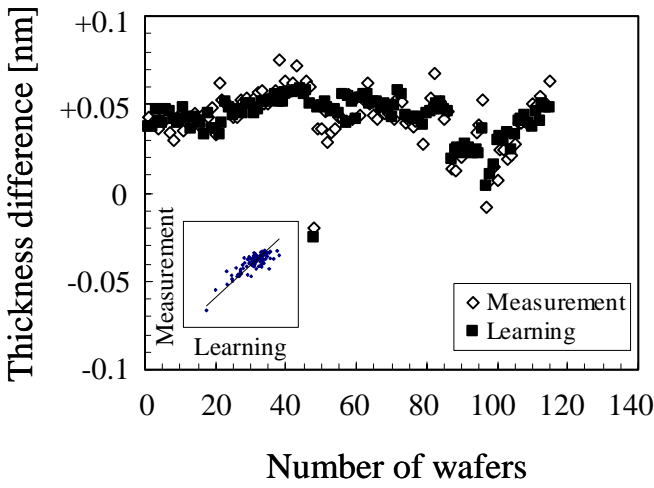


Fig. 2

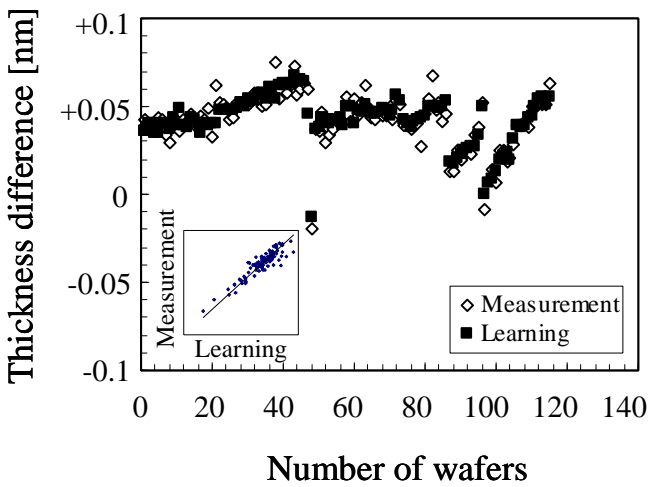


Fig. 3

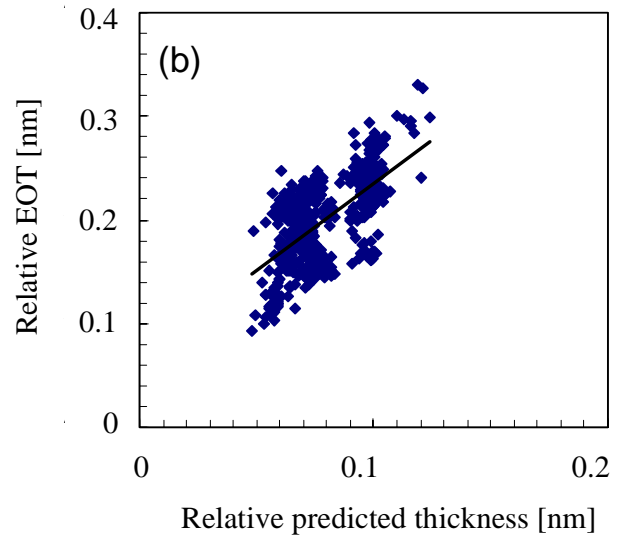
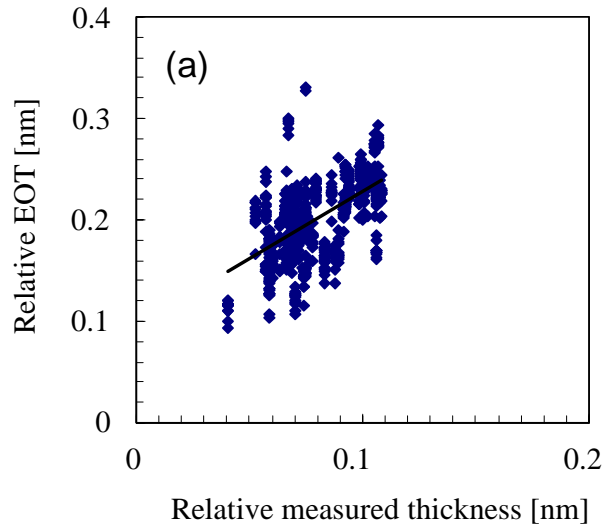


Fig. 5