Scheduling of Foreline Maintenance on a CVD Tool
Based on FDC Parameter

G. Hayderer¹, M. Radl¹, P. Scheibelhofer¹,², E. Stadlober², H. Purwins³,⁴, T. Purwins³ and D. Gleispach³(Presenter)
¹austriamicrosystems AG, ²Graz University of Technology, ³PMC Technologies, ⁴MGT Universität Pompeu Fabra Barcelona

Motivation

The semiconductor industry is continuously facing four main challenges in equipment and process behavior: accuracy, speed, throughput and flexibility. Therefore the semiconductor industry is interested to develop methods and strategies to predict equipment failures or malfunctions. Condition-based maintenance attempts to evaluate the condition of equipment by performing continuous (online) equipment condition monitoring. The ultimate goal is to perform maintenance at a scheduled point in time when the maintenance activity is most cost-effective and before the equipment loses optimum performance. This is in contrast to time- and operation count-based maintenance, where a piece of equipment gets maintained whether it needs it or not. This work was performed as part of the ENIAC project IMPROVE (Implementing Manufacturing science solutions to increase equipment productivity) and fab performance). Funding by the EU and the FFG is gratefully acknowledged.

Description

The study was performed on a CVD tool using FDC (fault detection and classification) data. In the first approach we set up a DOE where we generated artificially one specific failure in different magnitudes. FDC data were collected and a multivariate study has been performed by Support Vector Machines (SVM). For the second approach we collected data from a real production period. During the observation period the trap of the CVD tool filled up which has a negative impact on the equipment behavior as well as on the film performance. Using only the mean value during the deposition of the parameters foreline pressure and throttle valve step we developed an early warning system by a linear regression model so that we can plan the maintenance activities just in time.

Fault Detection by Support Vector Machine

For detecting and predicting unexpected variations in the throttle valve position we use a simple approach of historic trend analysis. For our analysis we take the throttle valve position data as reference and use a linear regression model to estimate the trend: $\hat{E}[\text{Valve}[i]] = a + b*i$. A typical data set for the mean of the throttle valve position per wafer is shown in Fig. 1. It is clearly visible, that it cannot adjust control limits to the chart without facing a huge amount of false alarms because of single wafer events. Therefore we analysed the behaviour of the trend in a historical data set, where six different excursions (Ex1 to Ex6 indicated in Fig. 1) are investigated. An optimum number of wafers to be used for the linear regression model is calculated to be 99. In this range of 99 wafers we estimate the linear trend in the data and check if the trend is above an appropriate control limit. This control limit is derived from the minimal slope of the trend that led to an excursion in previous cases. The estimated slopes of the regression model in a 99 wafer range is shown in Fig. 2. For the prediction of an excursion we can use the set of control limits in the newly derived chart. Combining this result with the indicator for the foreline pressure we are able to classify and to detect the failure mechanism and we can schedule corrective actions.

Fault Detection by Linear Regression

For detecting and predicting unexpected variations in the throttle valve position we use a simple approach of historic trend analysis. For our analysis we take the throttle valve position data as reference and use a linear regression model to estimate the trend:

$\hat{E}[\text{Valve}[i]] = a + b*i$.

A typical data set for the mean of the throttle valve position per wafer is shown in Fig. 1. It is clearly visible, that it cannot adjust control limits to the chart without facing a huge amount of false alarms because of single wafer events. Therefore we analysed the behaviour of the trend in a historical data set, where six different excursions (Ex1 to Ex6 indicated in Fig. 1) are investigated. An optimum number of wafers to be used for the linear regression model is calculated to be 99. In this range of 99 wafers we estimate the linear trend in the data and check if the trend is above an appropriate control limit. This control limit is derived from the minimal slope of the trend that led to an excursion in previous cases. The estimated slopes of the regression model in a 99 wafer range is shown in Fig. 2. For the prediction of an excursion we can use the set of control limits in the newly derived chart. Combining this result with the indicator for the foreline pressure we are able to classify and to detect the failure mechanism and we can schedule corrective actions.

Conclusion

Two studies have been performed on FDC data of a CVD tool for scheduling of foreline maintenance. A DOE has been performed where we studied the cross section of the foreline. Three FDC data sets with 13 indicators of at least 300 wafers each were investigated by means of a SVM (Support Vector Machine). We could show that a multivariate model is capable to predict failure even if we do not take into account the most sensitive sensors foreline pressure and throttle valve position.

With a Linear Regression Model of real data (both before and after equipment excursion), we could show that it is possible to use a univariate (SVM) chart with adequate control limits to predict failure. The sensor throttle valve position has been used to calculate its mean during deposition for this study.