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

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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 conditioning 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 looses optimum performance. This is in contrast to time- and/or 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 (SVMs).

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 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:

$E[valve[i]] = a + b*i$.

A typical data set for the mean of the throttle valve position per wafer is shown in Fig. 1. It is clearly visible, that we 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.

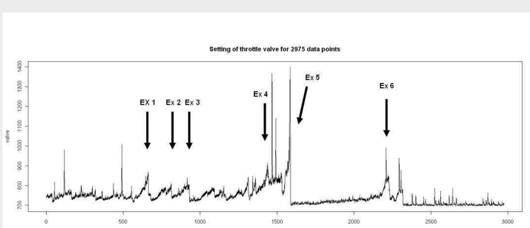

Fig. 1: Mean of throttle valve position for 3000 wafers. Ex1 to Ex6 indicates six tool excursions.

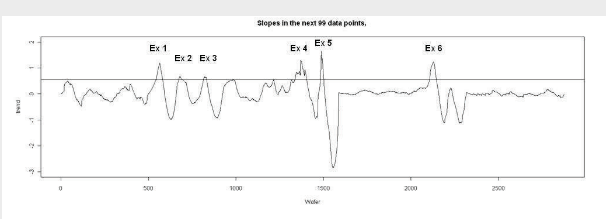

Fig. 2: Slope (b) of the linear regression model for the data set of Fig. 1 Appropriate control limits are shown.

Fault Detection by Support Vector Machine

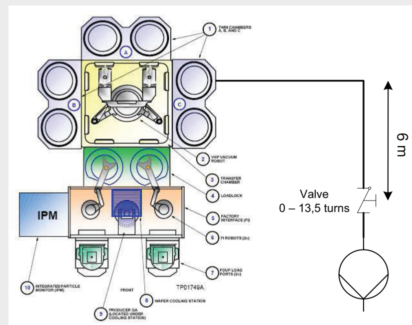

Fig. 3: Schematic Drawing of Experimental Set Up

We detect failures in the artificially generated failure scenarios K70, K80, K95, based on different feature subsets. K70, K80 and K95 represent the three scenarios, which denotes different valve positions in the foreline of the CVD tool. K95 denotes the most closed foreline, and therefore the largest magnitude of failure.

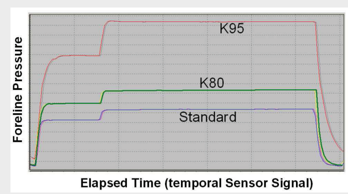

Fig. 4: Temporal signal of feature *foreline pressure* for three scenarios

Each production state is represented by a 14-dimensional sensor vector. The following attributes are considered: *foreline pressure (mean power on), throttle valve step (area step 2, range step 3, mean power on), chamber pressure reading (mean step 2, range step 2, range step 3, area step 2, mean power on), current recipe step time (max), heater AC current sensor (mean power on), HRF delivered/ reflected power (mean power on), susceptor temp (mean power on).*

For the three scenarios we have the following numbers of instances (wafers): K70 (272 healthy, 12 failure states), K80 (288 healty,12 failure states), K95 (298 healty, 12 failure states).

For failure detection we employ the support vector machine (SVM), a popular classification tool that uses large margins of hyperplanes to separate the data space into several classes. Also non-linear functions, e.g. radial basis functions, can be used to obtain more complex separations. A cost parameter trades off between misclassification and complexity of the classifier. In Table 1, we show the average f-measure of leave-one-out cross validation with a linear SVM on various feature sets. The best performance for cost parameter of 100, 10, 1, 0.1 of the SVM is displayed in Table 1. In general, linear kernels perform better, possibly due to the relatively small number of failure instances. Whereas any foreline pressure related sensor feature alone yields perfect detection in all three scenarios, neither foreline pressure related nor throttle valve step related sensor features are necessary to perform perfect failure detection in the K95 failure scenario.

Table 1: Sensor feature sets and failure detection performance for failure gravity in K70, K80, K95. In all scenarios of failure severity, any sensor feature related with foreline pressure is sufficient to detect the failure. Omitting sensor features related with foreline pressure and throttle valve step yields perfect detection in the K95 scenario as well. As a comparison, random detection yields 50 % average f-measure.

Attribute	K70			K80			K95		
foreline pressure: mean power on	x			x			x		
throttle valve step: area s2, range s3, mean power on		x			x			x	
chamber pressure reading: mean s2, range s3		x	x		x	x			
chamber pressure reading: area s2		x	x		x	x		x	x
chamber pressure reading: range s2								x	x
chamber pressure reading: mean power on		x	x		x	x			
current recipe step time: max		x	x		x	x		x	x
heater AC current sensor 2: mean power on		x	x		x	x		x	x
HRF delivered/reflected power: mean power on		x	x		x	x		x	x
susceptor temp: mean power on		x	x		x	x		x	
av. f-measure (%)	100	50	50	100	50	50	100	98	100

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 reduced 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 just before and after equipment excursions, we could show that it is possible to use a univariate SPC 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.