# Predictive Maintenance for Improved Sustainability — An Ion Beam Etch Endpoint Detection System Use Case

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**Abstract.** In modern semiconductor manufacturing facilities maintenance strategies are increasingly shifting from traditional preventive maintenance (PM) based approaches to more efficient and sustainable predictive maintenance (PdM) approaches. This paper describes the development of such an online PdM module for the endpoint detection system of an ion beam etch tool in semiconductor manufacturing. The developed system uses optical emission spectroscopy (OES) data from the endpoint detection system to estimate the RUL of lenses, a key detector component that degrades over time. Simulation studies for historical data for the use case demonstrate the effectiveness of the proposed PdM solution and the potential for improved sustainability that it affords.

**Keywords:** PM, PdM, OES, RUL, Ion Beam Etch

## 1 INTRODUCTION

Sustainability has emerged as a result of significant concerns about the unintended social, environmental, and economic consequences of rapid population growth, economic growth and excessive consumption of natural resources. The consideration of sustainability has become an integral part of many industrial activities [1]. The benefits of sustainable energy and environmental management include better accountability, better control and allocation of cost, improved performance and reduction in waste. For the semiconductor manufacturing industry reliable and efficient maintenance schemes play an important role in improving sustainability as they increase the plant yield and reduce downtime and waste of energy and materials significantly [3]. Currently, time-based preventive maintenance (PM) strategies are widely used in the semiconductor manufacturing industry where maintenance is carried out periodically according to prior or historical knowledge of the process or equipment. However, PM is quite a conservative and yet insecure strategy as maintenances are usually performed well before the relevant failure while the true failure development is not monitored. Frequent PM activities also increase the cost as more energy, materials and uptime are wasted by the maintenance activities, which impacts negatively on the environment.

Considering the disadvantages of PM, the concept of predictive maintenance (PdM) was proposed where maintenance actions are taken only when necessary and maintenance tasks can be optimally scheduled so as to improve efficiency and reduce waste

[4]. PdM utilizes all available data sources from the process to develop predictive models for remaining useful life (RUL) estimation of key equipment components which need to be maintained. These data sources for PdM can be from existing sensors, test sensors and test signals [5]. A broad range of data mining and machine learning methods can be used for data pre-processing, feature extraction/selection and health model development for PdM [2, 3]. For example, regularization methods are used to identify health predictive models for ion-implantation in [6] and Bayesian networks, random forest and linear regression modelling methods are compared in [2] for PdM on an implanter system. Generally speaking, there exists an ongoing shift from traditional PM approaches to PdM schemes in the semiconductor manufacturing industry [7].

Echoing the advances in PdM technologies and the need to improve sustainability by reducing the waste of energy and materials, this paper studies the development of an online PdM module to replace the existing PM scheme for the lens used in the endpoint detection system of an ion beam etch tool used in semiconductor manufacturing. The developed PdM module uses the existing optical emission spectroscopy (OES) data from the endpoint detection system to estimate the RUL of lenses, a key component that degrades over time. The rest of the paper is organized as follows: Section 2 briefly introduces the ion beam etch process and the corresponding maintenance task; Section 3 describes the proposed online PdM module for the lens used in the endpoint detection system; Section 4 details the experiments and simulations used to evaluate the proposed PdM lens RUL estimation module; Finally, some conclusions are drawn in Section 5.

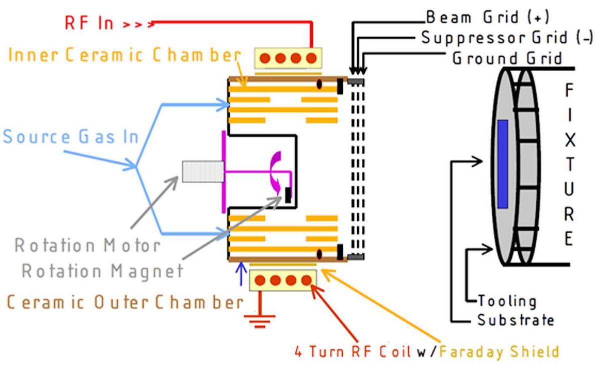


**Fig. 1.** Overview of an ion bean etch tool

## 2 Ion Beam Etch and Maintenance Task

Ion beam etch is a versatile etch process for pattern delineation and material modification in which the substrate to be etched is placed in a vacuum chamber in front of a broad-beam ion source. The diagram of the considered ion beam etch tool is shown in

Fig. 1. The magnetic field for the ion source is created by a cylindrical solenoid RF coil. High ionization efficiency is achieved as the electrons generated by the source follow a circular path that has been designed so that the electrons have a high probability of collision with the process gas molecules that fill the plasma chamber. Three grid plates which are separated with ceramic insulators are used to extract ions from the source and accelerate them towards the wafer as beams. The wafer is held in place by clamp claws and the fixture can rotate or tilt to change the mill angle in order to optimize the smoothness of the etch.

An endpoint detection system is often fitted as an integral part of ion beam etch tools. This system uses an optical sensor to capture light emission from the chamber, performs OES to obtain the spectral decomposition of the light, and then analyzes the resulting spectrum to determine the endpoint of each etch run. Fig. 2 shows the main components of the interface between the endpoint detection system and the chamber. Here one key component is the lens which acts as the light pathway.

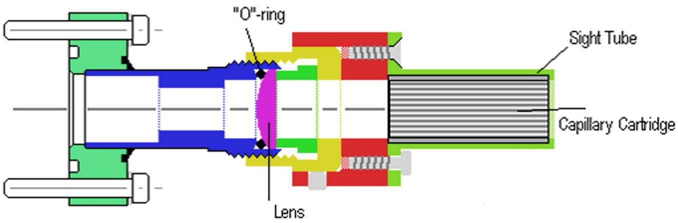


**Fig. 2.** Components used in the endpoint detection system

The quality of the collected OES data influences the accuracy of endpoint detection and thus it is vital to guarantee the reliability of the measured OES data for the ion beam etch process. However, the lens as well as the capillary used in the endpoint detection system becomes dirty/degrade over time. In particular, as dirt builds up on a lens its opacity increases and this reduces the amount of light reaching the OES sensor and hence the intensity of the recorded OES data. Thus, it follows that if we can track these changes over time we can generate a health index for lenses that can potentially be used to predict their RUL. This is enabled by collecting and analyzing OES data from monitor wafters, which are blank aluminium wafers processed periodically in the chamber as a pre-conditioning etch step before processing of production wafers. These monitor wafers undergo a fixed processing recipe and hence identical input conditions. Therefore, changes observed in monitor wafer OES signals over time are largely driven by changes in tool health.

Dirty lenses need to be replaced before they degrade to a point where they impact on tool performance. Currently this is done as part of a PM scheme, with the frequency of replacements determined by process engineers based on past experience of lens-related process failures. As such, many lenses are replaced prematurely due to the use of a conservative PM strategy. In the following an online PdM module is proposed that enables much better utilisation of lenses.

## 3 The Online PdM Module

Making use of the OES data from monitor wafers and the computing capabilities from the endpoint detection system, the proposed online PdM module is shown in Fig. 3. At each time instant, the OES data consists of the chamber light emission intensity recorded at 1201 distinct wavelengths. Thus the complete OES data for each monitor wafer etch run is an $m \times 1201$ matrix, where $m$ is the number of sample points.

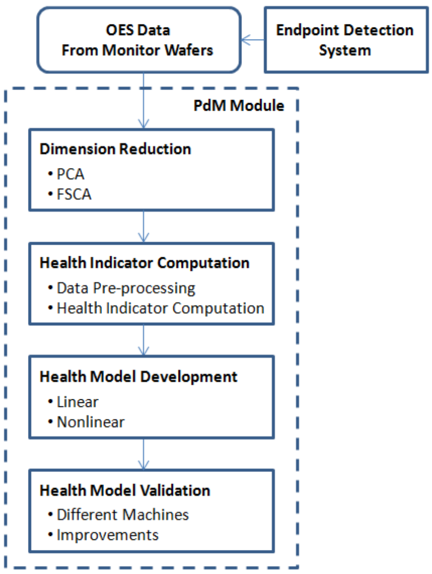


**Fig. 3.** The online PdM module

Using dimensionality reduction techniques the raw high-dimensional OES data can be reduced to one dimension. Here, principal component analysis (PCA) and forward selection component analysis (FSCA) are investigated for dimension reduction [8, 9]. The reduced data is further pre-processed and a single health indicator for the lens is computed for subsequent health model development. Based on the trend of the computed health indicator over multiple etch runs, linear and nonlinear models can be identified for real-time lens RUL estimation. The simplicity of the resulting lens health model allows it to be easily applied to different machines. In addition, the online PdM module can continuously update the prediction model for better RUL estimation using additional information from the expanding production history and maintenance records.

## 4 Experiments and Simulations

The experiments were conducted using OES data collected for 1746 monitor wafers processed on a Seagate® ion beam etch process from February to June 2013. The OES data for a typical monitor wafer (each one a $170 \times 1201$ matrix) is plotted in Fig. 4. Each peak corresponds to a chemical species present in the plasma. As can be seen, only a limited number of channels have peak values that are significantly greater than zero, which is a reflection of the relatively simple chemistry of the ion beam etch process during monitor runs.

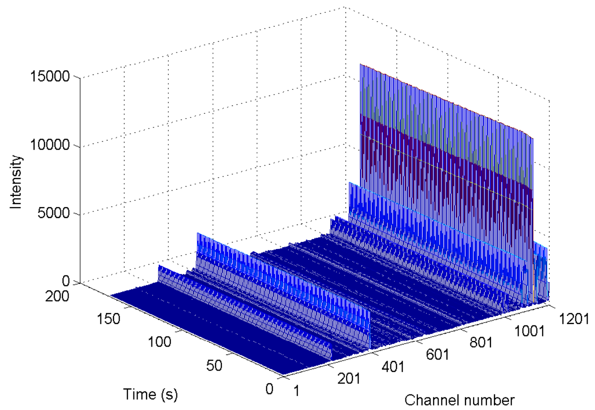


**Fig. 4.** The channel intensity over time for a typical run

### 4.1 Dimension Reduction and Health Indicator Computation

As seen in Fig. 4, the collected high-dimensional OES data for the typical monitor wafer is highly redundant enabling dimensionality reduction to be applied with minimum information loss. There are two main approaches for reducing dimensionality [8]: feature extraction methods such PCA which find a new set of $k$ dimensions that are combinations of the original $d$ dimensions and variable selection methods such as FSCA which select $k$ of the $d$ dimensions that best represent the information in the full $d$ dimensional dataset. Here PCA is performed on the dataset to demonstrate the suitability of using OES data for estimating lens RUL and FSCA is performed on the dataset to identify the key channels for health indicator computation in practice.

Combining the dataset together temporally and performing PCA on the resulting $2968210 \times 1201$ dimension matrix yields the scores for the first principal component (PC) as plotted in Fig. 5. Here, the color of the scores changes from black to red to reflect the evolution of time (used later). The first PC accounts for 98.49% of the data variability confirming that the original OES data are highly redundant and that PCA can successfully reduce the dimension with little loss of information. Cross-checking the patterns in this plot against maintenance logs revealed that the two biggest jumps in score corresponded to the maintenance events where a capillary change along with lens change occurred, while all the other jumps highlighted by blue lines corresponded to lens changes. Thus two patterns are evident. The first is a long term trend linked to the aging of the capillary. Superimposed on this is a short term trend linked to lens deterioration. Thus, it can be concluded that the PCA score plot effectively captures the evolution of the OES data over time and the score contains a clear lens and capillary health signature.

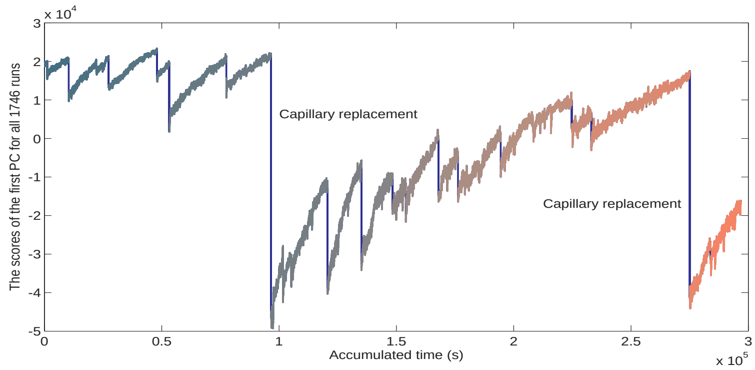


**Fig. 5.** The scores of the first PC for all 1746 runs

In order to facilitate the health indicator computation and link the health indicator with physical signals rather than the scores from PCA, FSCA is performed on the dataset to identify the key channels that account for most data variability. FSCA is an extension of forward selection regression for selecting a subset of variables that best represent the original full set of variables [9]. This is equivalent to selecting successive components whose combination with the previously selected components explain the most variance across all the data. The components selected by FSCA are the most important features. Performing FSCA on the $2968210 \times 1201$ temporally combined dataset, channel 995 is selected as the most representative channel accounting for 98.48% of the data variability. The intensity evolution for the selected top channel is plotted in Fig. 6 for all 1746 runs. Similarly to Fig. 5, maintenance activities as well as lens deterioration are clearly reflected in the intensity changes of the channel. Therefore, only the OES data from this channel is needed for health indicator computation.

The OES data of channel 995 for each monitor wafer is a 170 sample time-series signal from which a single health indicator value needs to be computed. Here, this is achieved by defining the mean intensity of the time-series as the health indicator. Fig.

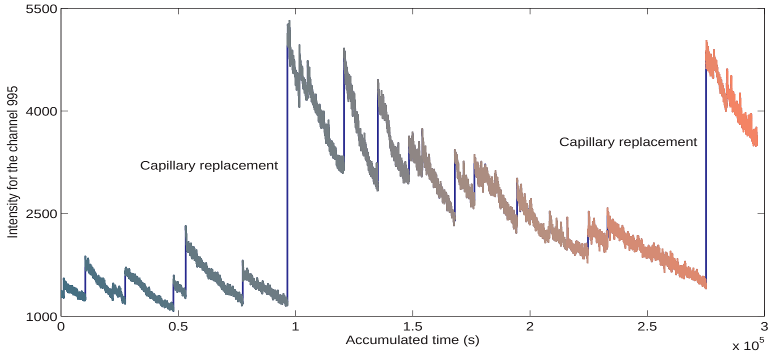


**Fig. 6.** The intensity evolution of the most representative channel as selected by FSCA

7 shows a plot of this health indicator for all 1746 processing runs. As can be seen it retains the lens and capillary health signature observed in the raw data.

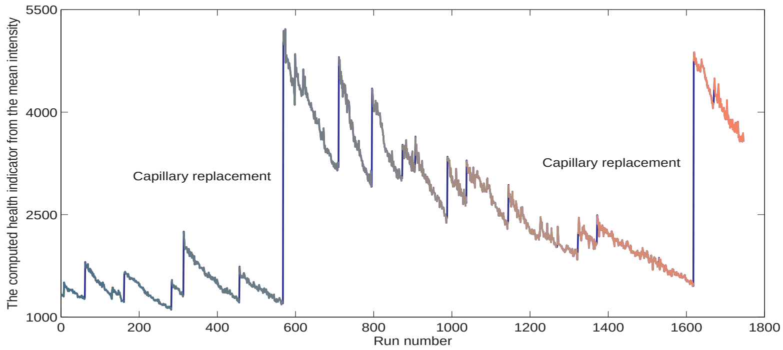


**Fig. 7.** The health indicator values for all 1746 runs

### 4.2 Estimating RUL of Lenses

Based on the jumps in the computed health indicator values in Fig. 7, 20 lens changes can be identified and the identified locations are consistent with the maintenance logs. The evolution of the health indicator tends to be linear over the life of each lens. In order to confirm this characteristic, the 20 lenses are plotted in parallel together with their linear approximations in Fig. 8. The time sequence of the lenses is conveyed through the color changing from black to red over time. It can be seen from Fig. 8 that the

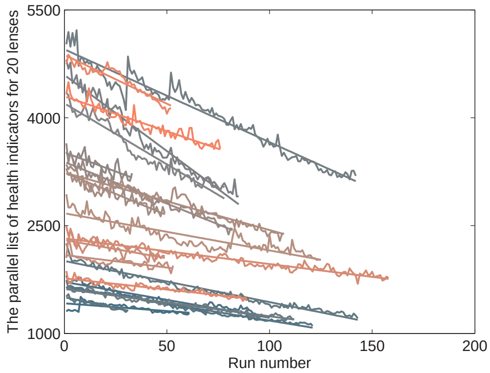


**Fig. 8.** The health indicator signal evolution for 20 lenses

starting point and slope of every lens health indicator evolution are different and thus a single generic linear model will not work for all lenses. Instead a new model needs to be identified online for each lens to fit its specific linear trend. The model for each lens can be identified and updated at each run using the health indicator values from previous runs and the RUL of the lens can then be predicted, where the RUL is defined as the number of runs required for the health indicator to drop below a specified threshold.

Taking the 3rd lens in Fig. 8 as an example, the threshold is set to be the health indicator value at run 100, then the prediction using a linear model at run 50 and 75 are shown in Fig. 9, respectively. The predicted run number at 50 is 98 with an error of -2% while the predicted run number at 75 is 91 with an error of -9%. The RUL of this lens at other run numbers can be computed in a similar way and the computed profile starting from run 20 is shown in Fig.10 with the comparison to the actual RUL. Similarly, the RUL of all other lenses can be predicted at any run number. The prediction errors at run 50 and 75 in terms of run number and health indicator value for the 6 lenses with a life greater than 100 runs are listed in Table 1, where the threshold is also set to be the health indicator value at run 100. Specifying the lowest health indicator value of these 6 lenses as the common threshold to reach, the life of the 6 lenses can be extended by an average of 137% if a PdM rather than a PM strategy is employed (i.e. average lens utilisation is only 42% with the adopted PM strategy).

It can be seen from Fig. 10 that the estimated RUL of lenses tends to be conservative at later run numbers as the trajectory for the health indicator strays away from its linear approximation, as shown in Fig. 9. Nonlinear models such as a polynomial model can be used instead of the linear model to improve the accuracy of the estimation. For example, using a third-order polynomial model to estimate the RUL of this lens at run 75 gives an error of 3% compared to the -9% obtained with the linear model. In practice, multiple models can be applied for online estimation and the most suitable model selected at each run number based on the former prediction errors and prior knowledge on the evolution of health indicator values.

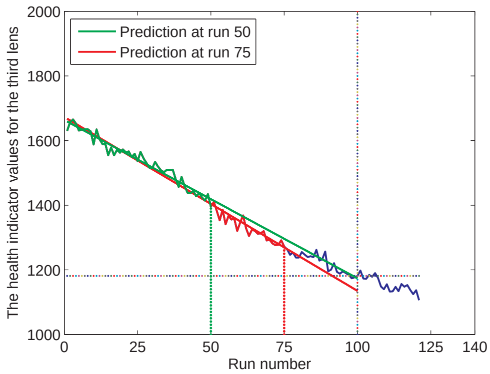


**Fig. 9.** The linear prediction for the 3rd lens

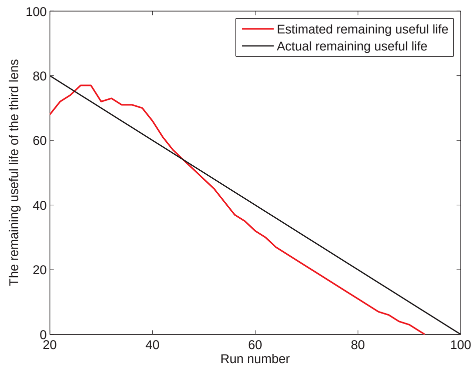


**Fig. 10.** Remaining useful life of the 3rd lens

**Table 1.** The prediction errors in terms of run number and health indicator value at run 50 and 75

| Lens ID | At Run 50 | | At Run 75 | |
|---|---|---|---|---|
| | Number_100 | Indicator_100 | Number_100 | Indicator_100 |
| 3 | 98 (-2%) | 1174 (-0.6%) | 91 (-9%) | 1135 (-3.9%) |
| 5 | 83 (-17%) | 1271 (-9.4%) | 91 (-9%) | 1344 (-4.2%) |
| 6 | 79 (-21%) | 1145 (-8.2%) | 95 (-5%) | 1127 (-1.6%) |
| 7 | 90 (-10%) | 3491 (-3.7%) | 112 (12%) | 3767 (3.9%) |
| 13 | 124 (24%) | 2543 (6.6%) | 122 (22%) | 2533 (6.2%) |
| 17 | 83 (-17%) | 1861 (-4.4%) | 88 (-12%) | 1894 (-2.7%) |

# 5 CONCLUSIONS

This paper has demonstrated that an online PdM module can be developed for the ion beam etch endpoint detection system with limited extra effort by making full use of available data sources and existing computing capabilities. Data mining techniques such as PCA have been used to develop the health model for the PdM module. The developed PdM module can issue maintenance alerts based on real-time predictions of RUL of lenses derived from analysis of OES data collected during the processing of monitor wafers. This enables maintenance activities to be optimally scheduled to reduce the waste of energy and materials, thereby improving sustainability. As such lens utilisation approaching 100% can be achieved with PdM (compared to a utilisation level of 42% with PM).

In general, the development and integration of similar online PdM modules using existing data sources, such as those provided by supervisory control and data acquisition (SCADA) and condition monitoring systems (CMS), can be an economic and sustainable practice in the semiconductor manufacturing industry and in many other manufacturing sectors as well.

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