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Remaining Useful Life Estimation of Lenses for an Ion Beam Etching Tool in Semiconductor Manufacturing Using Deep Convolutional Neural Networks

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Abstract. Maintenance plays a significant role in semiconductor manufacturing as plant yield, factory downtime and operation cost are all closely related to maintenance efficiency. Accordingly, maintenance strategies in semiconductor manufacturing industries are increasingly shifting from traditional preventive maintenance (PM) to more efficient predictive maintenance (PdM). PdM uses manufacturing process data to develop predictive models for remaining useful life (RUL) estimation of key equipment components. Traditional approaches to building predictive models for RUL estimation involve manual selection of features from manufacturing process data. This paper proposes to use deep convolutional neural networks (CNN) for the task of estimating RUL of lenses for an ion beam etch tool in semiconductor manufacturing. The proposed approach has the advantage of automatic feature extraction through the use of convolution and pool filters along the temporal dimension of the optical emission spectroscopy (OES) data from the endpoint detection system. Simulation studies demonstrate the feasibility and the effectiveness of the proposed approach.

Keywords. Predictive maintenance; remaining useful life; optical emission spectroscopy; convolutional neural networks.

1. Introduction

Semiconductor manufacturing has evolved from laboratory-like manufacturing plants to ultra-clean, highly automated and computerized facilities. The investment for such complex facilities is enormous and modern semiconductor manufacturing plants often operate in a continuous manner [1]. Reliable and efficient maintenance schemes reduce downtime and improve competitiveness of semiconductor manufacturing industries [2]. Tra-

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ditional preventive maintenance (PM) strategies usually conduct maintenance operations well before the relevant failures since the development of true failures is not monitored.

Predictive maintenance (PdM) strategies aim to schedule and conduct maintenance operations in an optimal way [3]. Process data from existing sensors, test sensors and test signals are used by PdM to build predictive models for remaining useful life (RUL) estimation of key equipment components [4]. Data pre-processing, feature selection and health model development in PdM can be implemented by various machine learning algorithms. For example, health predictive models were identified by regularization methods for ion-implantation [5]; kernel recursive least squares was used to formulate an online PdM approach for semiconductor equipment [6]; a virtual metrology-based baseline predictive maintenance scheme was proposed to combine with fault detection and classification [7]; vibration-related failures were identified from a predictive maintenance dataset using supervised learning algorithms [8].

RUL of lenses for an ion beam etch tool in semiconductor manufacturing was estimated from a linear regression model, which was built for each lens based on the extracted health indicators from the raw optical emission spectroscopy (OES) data using feature extraction [9]. This paper proposes to use deep convolutional neural networks (CNN) for building the regression model from past lenses to predict RUL of new lenses, leveraging its end-to-end learning capability for the task of feature extraction and selection normally required with traditional regression models. The rest of the paper is organised as follows. Section 2 introduces related literature on RUL estimation. Section 3 specifies the problem settings including the ion beam etching process and the collected process data. The structure of the deep CNN used for RUL estimation is provided in Section 4. The corresponding experimental results are given in Section 5. Finally, Section 6 provides some conclusions and future work.

2. Related work

Degradation signals that are directly correlated with underlying physical transitions to failures are usually used to estimate RUL [10]. RUL can be obtained through the full life test, where the estimated RUL can be evaluated according to some prior prognostics or assessment algorithms [11]. Pecht and Jaai [12] categorized prognostic techniques as physics-of-failure, data-driven or hybrid. However, models for physics-of-failure usually require detailed knowledge of the manufacturing process which are not always possible to obtain due to substantial model uncertainties and sudden changes in system parameters [12]. For statistical data-driven approaches, the estimation of RUL can be based on either directly observed processes or indirectly observed processes [13]. Regression-based RUL models are commonly used due to their simplicity [9,14]. Neural network based modeling takes account of arbitrary degradation profiles and deep neural networks are increasingly applied to estimate RUL for complex processes [15,16,17]. Furthermore, convolutional neural networks (CNN) widely used in computer vision have also been applied to estimate RUL without the need for manual feature extraction [18,19,20].

3. Problem Settings

3.1. Ion Beam Etch in Semiconductor Manufacturing

Ion beam etch uses a vacuum chamber to etch the substrate. Figure 1(a) shows an ion beam etch tool and the cylindrical solenoid RF coil generates the magnetic field for the ion source. Ions are extracted and accelerated from the source towards the wafer as beams by three grid plates. Clamp claws hold the wafter in place and the fixture can be rotated or tilted for an optimal angle to smoothen the etch.

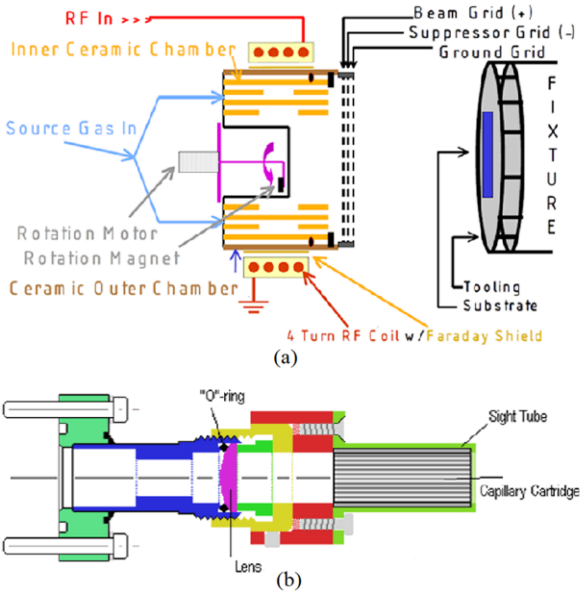

Figure 1. The ion bean etch tool and its endpoint detection system

An integral part of the ion beam etch tool is the endpoint detection system. An optical sensor is used in the system to capture light emission from the chamber, to obtain the spectral decomposition of the light, and then to analyze the resulting spectrum to determine the endpoint of each etch run. The lens and the capillary cartridge for the light pathway are the main components of the interface between the endpoint detection system and the chamber, which is shown in Figure 1(b). The accuracy of endpoint detection depends on the quality of the collected optical emission spectroscopy (OES) data. But the lens and the capillary cartridge used in the endpoint detection system can become dirty or degrade along with time, which reduces the amount of light reaching the OES sensor. Then the intensity of the recorded OES data can be reduced along with time as well. Such changes can be tracked from the collected OES data of monitor wafers. These monitor wafers are blank aluminium wafers processed periodically in the chamber as a pre-conditioning etch step before the processing of production wafers. As these monitor wafers undergo a fixed processing recipe, changes tracked in monitor wafer OES signals over time are largely driven by changes in tool health, which enables the estimation of RUL of lenses.

3.2. Optical Emission Spectroscopy Dataset

The raw OES data collected for each monitor wafer is in the form of a 170 × 1201 matrix consisting of 170 samples over time (1:1:170s) for each of 1201 channels (1:1:1201). Figure 2(a) shows the raw OES data for a monitor wafer run. Peak values correspond to the presence of certain ions while the chemistry of the ion beam etch process is relatively simple. For example, a snapshot of the channel intensity at 170s is shown in Figure 2(b) where the peak at Channel No. 1129 corresponds to Ar^+ and the peak at Channel No. 392 corresponds to Al^+.

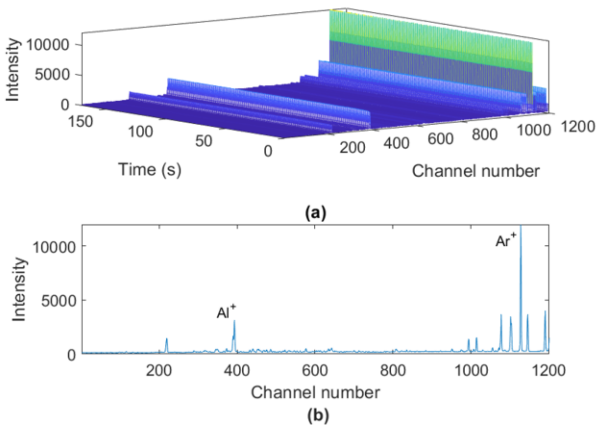

Figure 2. The OES data format for a monitor wafer

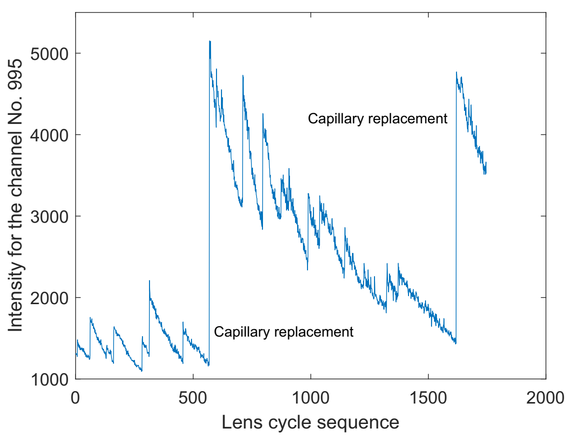

Figure 3. Maintenance operations indicted by the OES data

The raw OES dataset was collected for 1746 monitor wafers that were processed on an industrial ion beam etching process from 1st February, 2013 to 20th June, 2013.

The collected OES data is to be simplified by taking all the channel intensity data at the sampling time instant 170s for each monitor water, which reduces the dataset from the dimension of 170×1201 to 1×1201. This is due to the fact that the intensity for all channels tends to be constant on the time scale of a single monitor run (170s). The change of intensity for the channel No. 995 for these 1746 monitor wafers is shown in Figure 3. The corresponding maintenance operations can be mapped to the sharp jumps in intensity observed in Figure 3. The maintenance log as well as the dataset confirmed that there were two capillary replacements and 20 lens changes for this machine tool. These 20 lenses have varying life cycles ranging from 31 to 158. In order to develop the regression model for estimating RUL of lenses, the simplified OES data from these 20 lens changes is divided to a training dataset of 14 lenses and a testing dataset of 6 lenses.

4. Deep Convolutional Neural Network for RUL Estimation

The architecture of the deep CNN adopted in the study is similar to the one that is used in the literature [20], where a 1-D convolution is applied along the time sequence direction only. Thus the order of the channels does not impact the training and only trends in one channel at a time are considered. The dataset from 14 lenses are processed in a sequence format with the first dimension representing the number of channels and the second dimension representing the time duration or the length of lens cycle sequences. The deep CNN consists of five consecutive sets of a 1-D convolution layer, batch normalization, and a relu layer to be followed by a fully connected layer and a dropout layer. A regression layer is the last layer for the network. The detailed architecture of the adopted deep CNN with the relevant parameters is listed in Figure 4. It is worth noting that the structure of the deep CNN as well as its parameters can be further adjusted to improve its performance.

```
 1   'sequenceinput'      Sequence Input with 1201 dimenstions
 2   'conv1d_1'           1-D Convolution (5,32)
 3   'batchnorm_1'        Batch Normalization
 4   'relu_1'             ReLU
 5   'conv1d_2'           1-D Convolution (7,64)
 6   'batchnorm_2'        Batch Normalization
 7   'relu_2'             ReLU
 8   'conv1d_3'           1-D Convolution (11,128)
 9   'batchnorm_3'        Batch Normalization
10   'relu_3'             ReLU
11   'conv1d_4'           1-D Convolution (13,256)
12   'batchnorm_4'        Batch Normalization
13   'relu_4'             ReLU
14   'conv1d_5'           1-D Convolution (15,512)
15   'batchnorm_5'        Batch Normalization
16   'relu_5'             ReLU
17   'fc_1'               Fully Connected (200)
18   'relu_6'             ReLU
19   'dropout'            Dropout (50%)
20   'fc_2'               Fully Connected (1)
21   'regressionoutput'   Regression Output (MSE)
```

Figure 4. The deep CNN structure for RUL estimation

5. Experimental Results

The deep CNN has been trained using 14 lenses and tested on 6 new lenses. The test data contain partial sequences of these 6 lenses and also the corresponding values of the RUL at the end of each sequence. The test dataset undergoes the same preprocessing steps as the training dataset. Taking testing lens No. 3 as an example, the predicted RUL using the trained deep CNN model is shown in Figure 5 where the estimated RUL can roughly follow the true RUL. A comparison to the traditional approach for the same lens is also included [9]. It can be seen that the trained deep CNN provides RUL estimation from the beginning of the lens while the traditional approach of [9] needs to collect some process data to build the local regression model for RUL estimation. However, the local regression model from [9] does have a better RUL estimation with a root mean square error (RMSE) of 6.9 while the current method has a RMSE of 15.6. The larger RMSE of the current method mainly comes from the beginning of the estimation and the trained deep CNN approaches a comparable accuracy for RUL estimation to the traditional approach at the later stage of the lens' life, which confirms the feasibility of using deep CNN for estimating RUL of lenses and also the importance of using local data to improve the accuracy of RUL estimation for both methods.

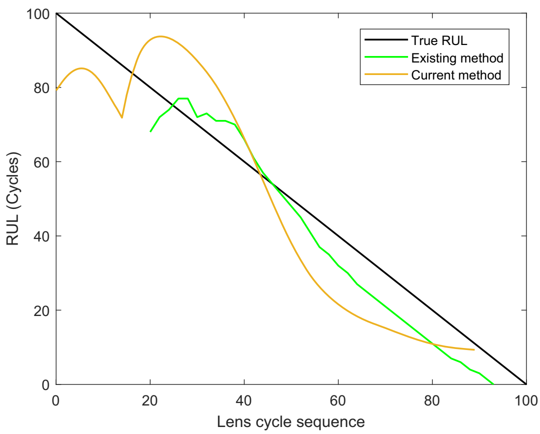

Figure 5. RUL estimation for testing lens No. 3

6. Conclusions and Future Work

This paper has studied the use of a deep CNN to estimate RUL of lenses for an ion beam etch tool in semiconductor manufacturing. The benefit of using a deep CNN is that it avoids manual feature selection from sensor data through automatic feature abstraction and extraction. However, the current approach uses the data from past lenses to build the regression model to estimate the RUL of new lenses without the use of new lenses' data for improving the model. In the future work, transfer learning could be applied to update the built regression model continuously so as to improve its accuracy for RUL estimation.

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