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Use of neural network to in situ conditioning of semiconductor plasma processing equipment

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ABSTRACT

A strategy for in situ fault detection of plasma equipment is presented. This was accomplished by combining optical emission spectroscopy (OES), neural network. The OES was used to collect fault spectra, inducted by radio frequency source and bias powers. A fault detection model was constructed by training the backpropagation neural network (BPNN) on the whole OES spectrum representing a normal plasma operation. The trained BPNN model was tested on the test data generated at other powers. The test result indicates that the BPNN model was capable of detecting abnormal plasma caused by a small variation of 1% in the source power. Due to less impact on the plasma properties, the BPNN model reacted sensitively only to a relatively large variation in the bias power. The performance of the BPNN model-based monitoring scheme was further compared to that of identified radicals. Much improved sensitivity of the BPNN model over them was clearly demonstrated for the source power variation. On the other hand, certain radicals yielded much improved detection for the bias power variation. This was manifest as plasma was monitored by means of the CUSUM control chart. In consequence, monitoring BPNN model-based prediction and identified radicals simultaneously is expected to provide an improved detection of plasma processing equipment.

1. Introduction

Plasma equipment is crucial in etching or depositing thin films for semiconductor manufacturing. Any occurrence of plasma faults severely degrades process quality and eventually device yield. Therefore, plasma status needs to be stringently monitored. As the pattern density increases, this is increasingly in demand.

To monitor plasma processes, a variety of in situ sensors have been utilized in manufacturing sites. These include a radio frequency (rf) impedance sensor, an optical emission spectroscopy (OES), an ion energy analysis system (IEAS), and a residual gas analyzer (RGA). Each sensor provides detailed and plentiful information effective in detecting abnormal plasma. The OES provides a spectrum that contains various radical intensities over a given wavelength range. The impedance sensor characterizes the electrical impedance of plasma in terms of the resistance and reactance components [1]. From an ion energy distribution, the ion energy analysis system extracts useful diagnostic variables regarding ion energy and flux [2]. This system was recently adopted not only to analyze ion bombardment impact on deposited film properties [3], but to build a monitoring scheme [4]. The residual gas analyzer provides the concentration of gas species. Of these, OES is the most popular in detecting faults in a plasma [5], monitoring etch endpoint [6] or wafer states [7]. For a given plasma process, OES yields a huge set of radical intensities at specific wavelengths. Radicals reacting sensitively to a change in process parameters are identified either relying upon in-depth chemical and physical knowledge or using a systematic data reduction technique. The performance of fault detection by the former approach is somewhat limited because diagnostic clues from other unselected radicals are disregarded. In general, fault symptoms are distributed across all radical intensities. It is not certain that PCA-reduced set of radicals well incorporates the nature of complex, nonlinear fault distribution. This concern may be circumvented by developing a technique to characterize a full set of radicals as investigated [8]. For real-time plasma monitoring, the PCA-reduced set of radicals are typically coupled with a time-series neural network modeling [9–11]. They are further utilized to build in-line models to track film properties on a wafer-to-wafer basis [12–14]. A challenge facing OES-based monitoring is to construct a prediction model with a complete set of radicals that has no corresponding set of responses. In order to develop a neural network model with a supervised learning, OES data need to be converted into another data composed of input and output variables. This has been typical to a neural network-applied time series modeling [4,9–11]. In this study, the same technique is used to prepare data for modeling. The next challenge is related to the preparation of fault patterns, on which the neural network is trained. However, it is hardly possible to collect OES

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patterns for all possible fault occasions. In this sense, a fault detection model not relying on intentionally simulated fault patterns is in demand. This is likely to be resolved as the model is built with normal OES data, which are collected during the normal operation of plasma equipment. Recently, as stated earlier, we have constructed fault detection models using the normal ion energy data and demonstrated their high detection accuracy [4]. The generalization power of neural network is likely to be the key contributor to the reported monitoring performance. To our best knowledge, this work addresses the first application of normal OES patterns to a neural network monitoring of faults in plasma states.

In this study, a new OES-based diagnosis model is presented. Experimental data were collected in a plasma. The data are modeled by using a backpropagation neural network (BPNN) [15]. The proposed OES model is clearly differentiated from earlier OES models in that it is trained on OES pattern collected during the normal operation of plasma equipment. It should be noted that previous models were trained on the entire fault pattern. The model is then coupled with a CUSUM control chart [16]. For a comparison purpose, OES spectra regarding the major radicals involved in the plasma process are also incorporated into the chart.

2. Experimental

In-situ OES data were collected in a SiH_4–N_2 plasma. A schematic of the plasma equipment employed is shown in Fig. 1. As shown in Fig. 1, a plasma is created inside a processing chamber as a radio frequency (rf) source power is supplied into the gas filled chamber. Plasma is electrically neutral and assumed to have equal number of ions and radicals. The source power plays a crucial role of controlling the density of generated plasma. Larger source power produces larger plasma density. The other bias power connected to the bottom of the chamber is used to control ion bombardment. Larger bias power causes enhanced ion bombardment onto the film surface. Any change in delivered source or power induces a considerable variation in plasma radicals or ions as well as their interaction with film surface. Therefore, both powers should be stringently monitored during the plasma process. In this study, OES was used to collect spectra of radical intensities over a wavelength range of 177.37–1100.01 nm. Two types of OES data for neural network learning and testing were collected. The process time was

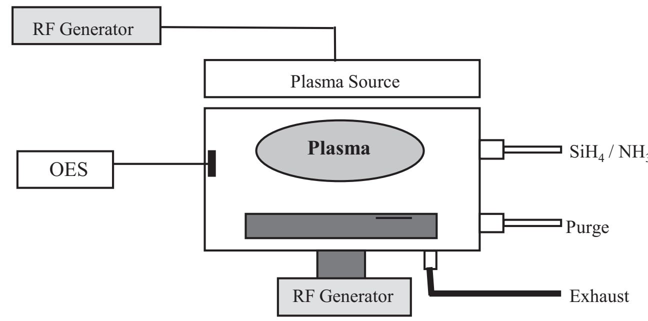

Fig. 1. Schematic of a plasma processing equipment.

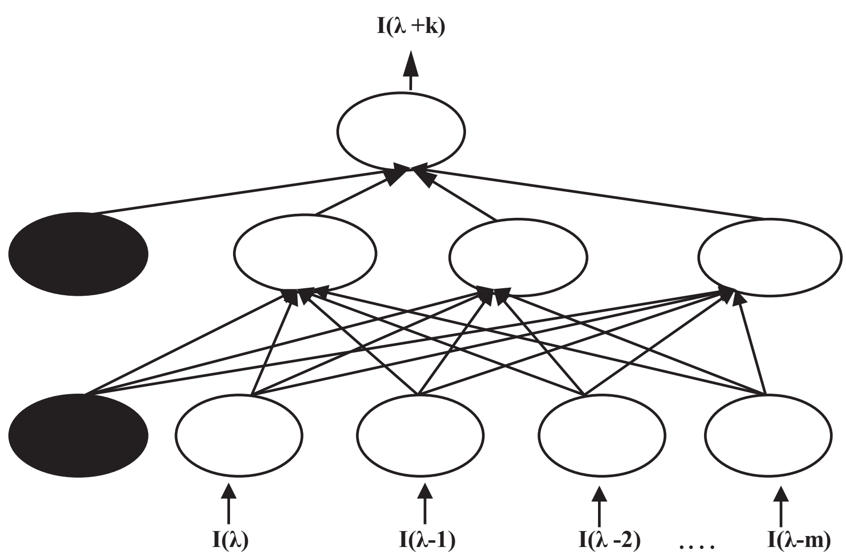

Fig. 2. Schematic of a backpropagation neural network.

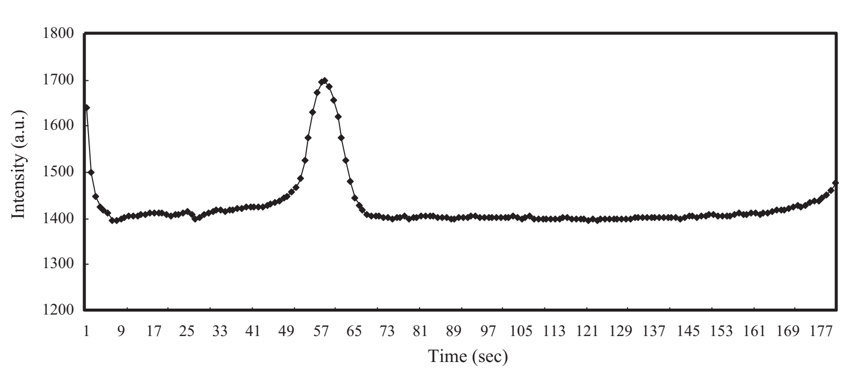

Fig. 3. Variation of average of radical spectra as a function of processing time.