ELSEVIER

journal homepage: www.elsevier.com/locate/jmatprotec

JOURNAL OF MATERIALS PROCESSING TECHNOLOGY

Prediction of plasma etch process by using actinometry-based optical emission spectroscopy data and neural network

*Byungwhan Kim**, *Minji Kwon*

Department of Electronic Engineering, Sejong University, 98, Kunja-Dong, Kwangjin-Ku, Seoul 143-747, Republic of Korea

ARTICLE INFO

Article history:
Received 17 August 2007
Received in revised form
21 April 2008
Accepted 8 June 2008

Keywords:
Optical emission spectroscopy
Backpropagation neural network
Training factors
Genetic algorithm
Plasma etching process
Principal component analysis
Actinometry
Model
Prediction

ABSTRACT

Optical emission spectroscopy (OES) data were used to construct neural network models of plasma etch process. According to a statistical experiment, actinomeric OES data were collected from the etching of oxide thin films in a CHF_3–CF_4 magnetically enhanced reactive ion etching system. The etch responses modeled include an etch rate, a profile angle, and an etch rate-nonuniformity. Principal component analysis was applied to reduce the dimensionality of OES data. Three data variances adopted are 98, 99, and 100%. For each data variance, backpropagation neural network models were constructed. The training factors optimized by genetic algorithm include the training tolerance, magnitude of initial weight distribution, number of hidden neurons, and two gradients of activation functions in the hidden and output layers. The presented models demonstrated much improved predictions over the previous ones. The improvements were 43, 61, and 17% for the etch rate, profile angle, and etch rate-nonuniformity models, respectively.

1. Introduction

Plasma etching is a key means to etch fine patterns in manufacturing integrated circuits. Many process parameters are involved in etching thin films such as an etching of silicon oxynitride film in an inductively coupled plasma (Kim et al., 2005a,b). Certain variations in them can cause a fault in plasma. To maintain a device yield and an equipment throughput, plasma processes need to be stringently monitored, diagnosed, and controlled. For these purposes, neural networks have been widely used to build a prediction model. Applying neural networks to model the plasma-processed data is advantageous in that they can learn complex input–output relationships accurately while producing a quick response. During a plasma etching, a variety of data might be acquired, including external process parameters, in situ diagnostic data, or surface film measurements. These data have been used to construct three types of neural network models. The first type of model attempted to relate the variations in external process parameters such as a radio frequency power to those in film measurements such as the etch rate. In the context of coatings of thin films or discharge processes, this

* *Corresponding author.*
E-mail address: kbwhan@sejong.ac.kr (B. Kim).
0924-0136/$ – see front matter
doi:10.1016/j.jmatprotec.2008.06.006

type of model has been used to model a photoluminescence intensity in a pulsed laser deposition process (Ko et al., 2005), a weld bead geometry in pulsed gas metal arc welding process (Manikya Kanti and Srinivasa Rao, 2008), a bulk behavior of coatings (Lee et al., 2007), a removal rate along with tool wear in electrical discharge processes (Mandal et al., 2007), or a plasma etching of silicon oxynitride (Kim and Lee, 2005). The second type of model was constructed to predict the variations in an in situ process parameter with the other ones (Hong and May, 2004). This model can be effectively used to monitor the states either in in situ process parameters or equipment chambers. The last, third type of model was used to learn certain relationships between X-ray photoelectron spectroscopy and etch surface roughness (Kim and Park, 2006). This type of model can be utilized to identity an anomaly in plasma states. The most popular in situ diagnostic instrument is an optical emission spectroscopy (OES). The OES provides detailed information regarding a number of radicals involved in plasma etching or deposition. This information was utilized to detect an etch endpoint (Stevenson et al., 1998). Using the backpropagation neural network (BPNN) (Rummelhart and McClelland, 1986), several attempts were also made to construct a control model of OES in a MERIE (Kim et al., 2005a,b) or a reactive ion etching (Hong et al., 2003) process. In these works, a principal component analysis (PCA) (Jackson, 1991) was used to reduce the dimensionality of OES input patterns. Rather than the reduced data, the nonreduced data were used and the resulting models demonstrated an improved prediction over those built with the reduced data (Kim et al., 2005a,b). However, this work is limited in that the effects of all possible training factors involved in the BPNN training could not be optimized. This is mainly attributed to the huge input dimensionality of OES data. As the effect of all training factors is optimized, an improved OES model may be achieved.

In this study, a prediction model of OES data was constructed. The presented models are clearly differentiated from the previous ones (Kim et al., 2005a,b) in that they were optimized as a function of all training factors. The optimization was conducted by combining the PCA, BPNN, and genetic algorithm (GA) (Goldberg, 1989). The GA was used to search for an optimized set of training factors. Depending on the data variance, three types of models were constructed and compared to the previous models. The presented technique was evaluated with the etching data.

2. Experimental details

Fig. 1 shows a schematic of a MERIE system used in the etching. The OES system consisted of a manochromator (M), a photomultiplier tube (PMT) and a photocounting system. The photocounting system again comprised a discriminator, a multi-channel scaler, a system controller (SC), and a personal computer (PC). The remaining HVS represents a high voltage supply. The emission signal delivered to the manochromator is decomposed with a resolution of 2 nm using a grating of 1200 grooves/mm. The decomposed signal is then fed to the PMT through a slit of 50 μm diameter. Optical emission spectra were collected over a wavelength between 2276 and 7918 nm with 2.5 nm resolution. An example of OES data is shown in Fig. 2. The data were collected at 300 W RF power, 50 Torr pressure, and 80 and 40 sccm for CHF_3 and CF_4 flow rate, respectively. In the context of plasma modeling, OES data is significant since they can provide detailed intensities for all possible radicals, serving as etchants or precursors to deposition. Moreover, their distributions are unique to each of process conditions. These two features make them attractive for plasma modeling. To maintain an actinometry, the raw OES data shown in Fig. 2 were divided by Ar intensity peaked at 7504 Å. The resulting data were also included in Fig. 2 and these were used as an input pattern in training neural network.

Test patterns were fabricated on (1 0 0) oriented silicon (Si) substrates. Oxide films of about 900 nm thick were deposited on chemically pre-cleaned (1 0 0) silicon by reacting SiH_4 with N_2O in a plasma-enhanced chemical vapor deposition reactor at 400 °C temperature and 3 Torr pressure. Using a spin coater, 1.02 μm thick photoresist-film was coated at the RPM of 4000, and subsequently soft-baked for 90 s at 90 °C temperature on the hot-plate in a track system. Photoresist patterns (thus holes) of equal lines and spaces were formed using an i-line Nikon stepper. Developed hole samples were subsequently hard-baked at 120 °C for 30 min in a convection oven.

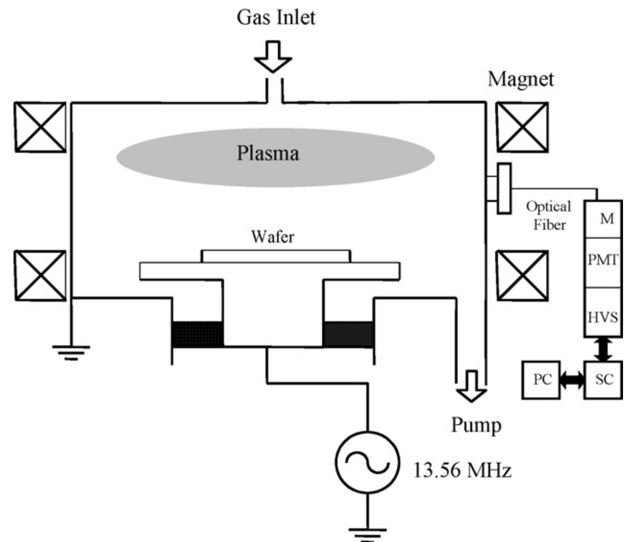

Fig. 1 – Schematic of a magnetically enhanced reactive ion etch system.

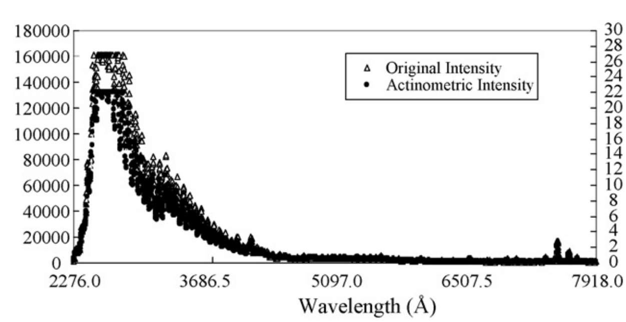

Fig. 2 – An example of actinometric OES data.