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Prediction of plasma processes using neural network and genetic algorithm

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Abstract

Using genetic algorithm (GA) and backpropagation neural network (BPNN), computer models of plasma processes were constructed. The GA was applied to optimize five training factors simultaneously. The presented technique was evaluated with plasma etch data, characterized by a statistical experimental design. The etching was conducted in an inductively coupled plasma etch system. The etch outputs to model include aluminum (Al) etch rate, Al selectivity, silica profile angle, and DC bias. GA-BPNN models demonstrated improved predictions of more than 20% for all etch outputs but the DC bias. This indicates that a simultaneous optimization of training factors is more effective in improving the prediction performance of BPNN model than a sequential optimization of individual training factor. Compared to GA-BPNN models constructed in a previous training set, the presented models also yielded a much improved prediction of more than 35% for all etch outputs. The proven improvement indicates that the presented training set is more effective to improve GA-BPNN models.

Keywords: Plasma etching; Backpropagation neural network; Genetic algorithm; Statistical experimental design

1. Introduction

Plasmas play a crucial role in etching and depositing thin films. To manufacture plasma processes in a cost effective way, computer prediction models are increasing in demand. First principle models are subject to many simplifying assumptions due to the lack of understanding of physical and chemical processes. As an alternative, an adaptive neural network has been used to build a prediction model of plasma processes [1–7]. Compared to physical models, neural network models are advantageous in that they do not require any assumptions while producing quick predictions. Among the various neural network paradigms, the backpropagation neural network (BPNN) [8] has been the most widely adopted in plasma modeling. Constructing a BPNN model is complicated by the presence of several training factors, including the hidden neurons, training tolerance, initial weight distribution, and function gradients [9,10]. In most applications, training factor effects are typically optimized by experimentally tuning each factor individually. However, it is expected that better predictive model might be achieved by adequately accommodating complex effects among the training factors. A training factor effect model [9,10] or a genetic algorithm (GA) [11] was used to find a set of optimized training factors [12,13].

In this study, GA is used to optimize training factors simultaneously. This work is an extension of the previous work [13] in that new training factors are involved in GA optimization. Another difference stems from the fact that the presented technique is applied to construct plasma etch models, not plasma-enhanced chemical vapor deposition (PECVD) models. The experimental data were collected

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during the plasma etching of silica thin films. The etch process was characterized by a statistical experimental design and the etch outputs to model include a silica profile angle, aluminum (Al) etch rate, DC bias, and Al selectivity. The etching was conducted in an inductively coupled plasma etch system.

2. Experimental details

Schematic diagram of an inductively coupled plasma etch system is shown in Fig. 1. The process chamber serving as a ground plane is pumped by a turbomolecular pump, and the pressure is controlled by a down stream throttle valve. Gases are introduced via a multihole shower head and radio frequency (RF) bias power operating at 13.56 MHz is fed to the lower electrode with the diameter of 8.5 in. via a matching network. The upper chamber section was modified by a ceramic cylinder, through which RF source power is coupled via a multiturn helical coil operating at 2 MHz. The cylinder is closed at the upper end by a grounded electrode.

Test patterns were fabricated on p-type silicon wafers of 5 in. diameter. A buffer-clad layer of about 25 μm was deposited by the flame hydrolysis deposition method. The core layer of 8 μm thickness was subsequently formed, which was formed as SiO_2–P_2O_5–B_2O_3–GeO_2. Here the percentages of P, B, and Ge were all less than 1%. After the evaporation of AlSi (1%) of about 400 nm, the waveguide was patterned using a contact aligner. The AlSi (1%) layer was first etched in a $BCl_3/Cl_2/CHF_3$ plasma using the Plasma Therm reactive ion etch system, where the RF power and pressure were set to 150 W and 10 mTorr, respectively. To remove the layer completely, the layer was subsequently 30% overetched and the resist was then solvent-stripped. Following this, the silica core layer was etched in a CF_4/CHF_3 plasma using a Plasma Therm 690 ICP etch system. The process parameters that were varied include a source power, bias power, and gas ratio. The total flow rate of gases, CHF_3 and CF_4, was set to 60 sccm and the flow rate of CHF_3 was varied from 10 to 50 sccm. The gas ratio was defined as the flow rate of CHF_3 divided by the flow rate of CF_4. To characterize the etch process, a 2^3 full factorial experiment [14] was used along with one center point. The experimental parameter ranges employed in the design are 100–800 W, 100–400 W, and 0.2–5.0, for the source power, bias power, and gas ratio, respectively. Additional six experiments were conducted to provide the test data for model evaluation. Consequently, a total of 15 experiments were conducted. The etch outputs modeled include a silica profile angle, aluminum (Al) etch rate, Al selectivity to silica, and DC bias. The data set prepared is advantageous in it that it enables us to differentiate model performance clearly, and in that it provides a sufficiently large number of etch outputs for evaluation.

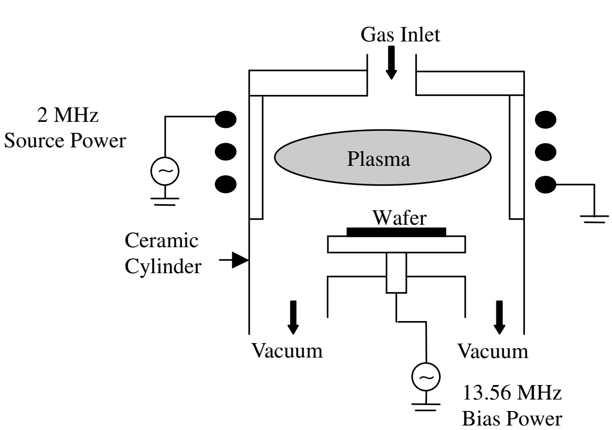

Fig. 1. Schematic diagram of inductively coupled plasma etch system.

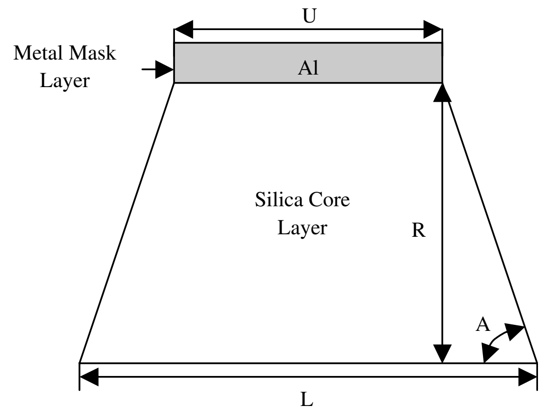

Fig. 2. Schematic diagram of etched pattern for measurements.

Using a Hitachi S800 scanning electron microscopy, the vertical etch rate of silica, R, was measured along with the vertical Al etch rate. The Al selectivity is defined as the silica etch rate divided by the Al etch rate. The profile angle (A) was estimated from the schematic of front view of etched silica film, depicted in Fig. 2. The A is defined as

$$A = \tan^{-1}\left[\frac{2R}{L-U}\right](^\circ) \tag{1}$$

where U and L represent the widths of the original and etched patterns, respectively. The remaining dc bias was measured by a DC volt meter embedded in a RF match network.

3. Neural network training factors

As shown in Fig. 3, the BPNN [8] consists of three layers of neurons: input layer, hidden layer, and output layer. The number of hidden layers was set to unity. This is because the BPNN containing one single hidden layer can encode any arbitrary complex input–output relationship [15]. A hidden neuron in the hidden layer performs a nonlinear feature extraction on the data provided by the input and output layers. Depending on the number of hidden neurons