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Development of Intregrated Process Control System for Plasma Etching utilizing Neural Network and Genetic Algorithm

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Abstracts The purpose of this study is to provide the integrated process control system, utilizing neural networl modeling, to search for the appropriate choice of control input, and to keep the process output within the desired rang in the real etch process.

Keywords Plasma Etching, Neural Network Modeling, Genetic Algorithm, Statistical Process Control

1. Introduction

Research in efficient modelings based on data obtained from experiments and manufacturing systems in DRAM production is rapidly progressing. In DRAM production lines, process is to maintain the fixed input with the varying outputs caused by natural effects as well as by abnormalities due to the measurement error, incorrect input setup, and raw material change. The outputs then results in moving away from the output tolerance. In order to improve the quality of DRAM products, it is essential to monitor process outputs consistently, and to correct the control inputs directly which affect process outputs.

The purpose of this study is to provide the integrated process control system, utilizing neural network modeling and genetic algorithm, to search for the appropriate choice of control input, and to keep the process output within the desired range in the real etch process.

Variations in the process output are classified as the drift and the shift. The drift is caused by a natural noise that changes over a period of time slowly and steadily, partly due to the aging of equipment. Although the drift moves the process output away from the target value, its variation is infinitesimal. On the other hand, the shift results in a larger variation due to the various causes and its width is normally greater than that of the drift. Without appropriate procedures, the process output will move away from the target value greatly. Therefore, the control strategy is to minimize the process shifts, in which process outputs are measured by monitoring wafers periodically[13].

2. Integrated Process Control System

The process control is to maintain the process outputs within the optimal target values during the process. In the present study, the integrated process control system is proposed to achieve this by implementing the process modeling and the process control together as shown in Fig. 2.1. The process control includes three controller modules, including Recipe Generator, Statistic Process Controller, and Feedback Controller.

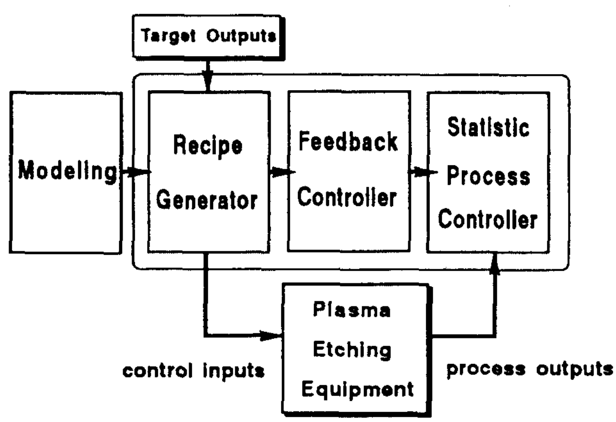

Fig. 2.1 The schematic diagram of intregrated process control system

2.1. Modeling of the Etching Process

The target process in this stydy is plasma etching, Fig. 2.2 shows the structure of multilayer neural network employed for modeling of plasma etching process. Eqs. (2-1)~(2-3) are the functional relationship between input layer, hidden layer and output layer. I, H, O are the output terminals of input layer, hidden layer, and output layer, respectively, and T represents teaching data. W and V represent connecting weights and α , β are the threshold values.

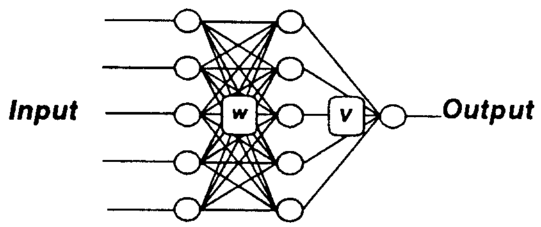

Fig. 2.2 The neural network model

$$I = T \qquad (2\text{-}1)$$
$$H = f\ (\ W\cdot I + \alpha\ ) \qquad (2\text{-}2)$$
$$O = f\ (\ V\cdot H + \beta\ ) \qquad (2\text{-}3)$$

Neural network adopts FFEBP (Feed Forward Error Back Propagation) algorithm for learning, which computes model output from the real input data, reduces the difference between the model output and the real output by gradient descent method and trains connection weights repeatedly until the difference reaches the value that users can satisfy.

The neural network modeling has sometimes the accurate predictive capability about the trained data only. To overcome this problem, we utilize both the training and testing data.

2.2. Search for the Optimal Control Input

For the target output of the process is determined, it is necessary to search for the optimal control input. For this, the neural network model with the genetic algorithm(Fig. 2.3) is employed.

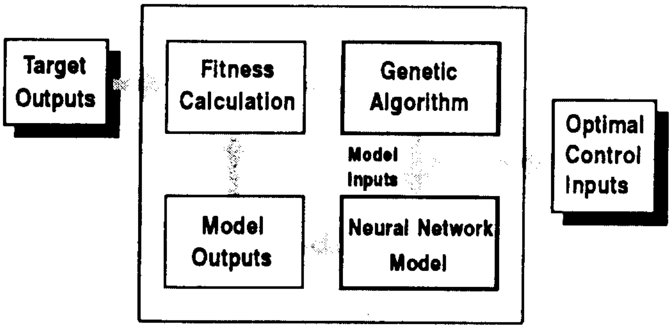

Fig. 2.3 The schematic diagram of tracking the optimal contol input.

For the target value of process output, the genetic algorithm generates many individuals at random, and all of them become the inputs to neural network. Each individual in genetic algorithm has the fitness F computed by Eq. (2-4), and repeats reproduction, crossover, and mutation. Such evolutions make the model output computed with individuals closer to the target output in search area. After predetermined generations, genetic algorithm selects the individual that has the closest model output to the target output as an optimal control input.

$$F = \frac{1}{\sum_{i=1}^{n} \| T_i - O_i \|}$$

(2-4)

where T_i is the target process output, O_i neural network model output, n the number of process output.

2.3. Statistical Process Control

If the control input is determined, then the process is prepared for run. The process output is measured periodically by the monitor wafer to detect the process shift due to abnormal cause. The process continues as long as abnormality is not detected. But if the shift detected, feedback controller returns the output on the optimal state and modifies the process modeling, selects new control input and compensates the process shift. In accomplishing this, it must be judged whether the process shift occurs. That is, among the numerous process fluctuations, it is necessary to classify the process shift and this classification is accomplished by statistical process control method.

Neural Network Model based SPC The existing stat- istical process control (SPC) chart is not effective because of the possibility of mis-alarm in integrated process control system. To make the best use of control chart (fault detection), the neural network model based SPC method is used.

The model based SPC, also known as generalized SPC, does not apply the process output to the control chart directly but the difference between the predictive model output and the measurment to the control chart.

$$\hat{y} = f\ (X)$$
$$y = \hat{y} + \varepsilon$$

(2-5)

where y is the measured output, $\hat{y}$ model output calculated through the process model, and X control input. Though the error ε includes both the expectation error of model and the pure noise, the standard deviation of ε is caused by the pure noise. The difference between the process output and the model output is a random sample in the normal distribution of ε, irrespective of control input under statistical control system[13]. Therefore, the model based SPC system adopted the Schwart control chart, which shows the difference and makes user detect assignable cause of process output regardless of the variations of the control input. Fig. 2.4 shows the schematic diagram of neural network model based SPC.

Control charts are classified as the moving average chart and the individual chart. The former needs the continuous experiments and their average error ε, but the later adjusts the error between model output and mesurements directly without averaging it. As the individual chart does not need time for averaging, it has merit to quickly detect the abnormality and disadvantage to increasing the possibility of misdetections. The present study adopts the individual chart.

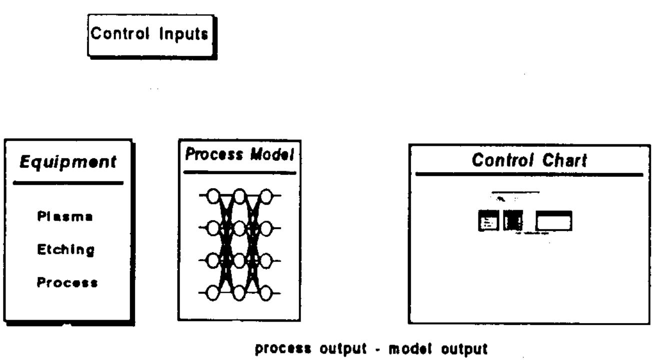

Fig. 2.4 Schematic diagram of NN based statistical process control

2.4 Feedback Controller

When the process shift occurs due to assignable cause, feedback controller is implemented to control the input to affect the process output and recover the process output to the optimal state. As shown in Fig. 2.5, it makes new modeling for the changes in process state due to assignable cause and selects the new control input that will be able to recover the process output on the optimal state.

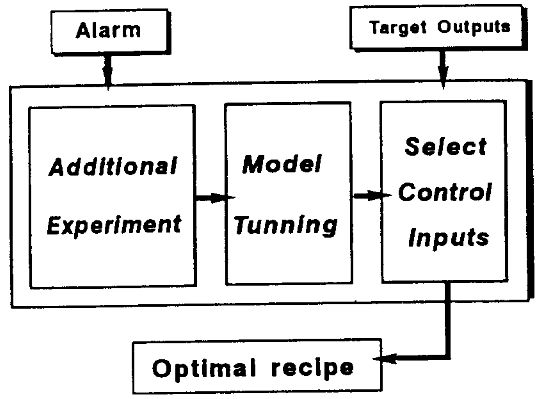

Fig. 2.5. The structure of the feedback controller

Model Modification To compensate the process shift by abnormality on the optimal state, the modeling and new control input are needed because the process state becomes different from the previous stable state. It needs input-output data of the shifted process state and means additional experiments of monitor wafers.

The modeling needs the same number of initial experiments if we use the same type of the initial neural network model as mentioned before. Also it needs much time and cost whenever the process shift occurs. Therefore, a new efficient model is desired to which requires less number of experiments as shown in Fig. 2.6. To minimize the number of parameters to be controlled, a multi-layered neural network model is designed to consist of two parts; one for the process model and the other for tuning. The process part represents the pure input-output relationships of the process and is formulated before the optimization step and independent of model modification. As a result, modeling is possible with a few experiments because the parameters in the model tuning part are needed to change in model modification.

Multi layer neural network model is designed for characterizing the abnormality occurred in the process. Incorrect input setting or measurement error of input generate the process shift.

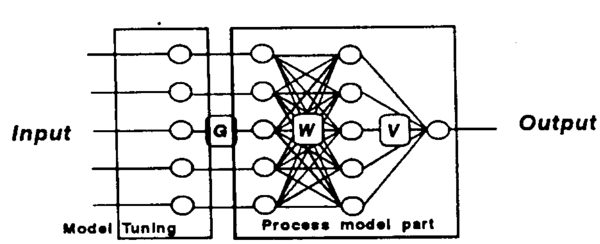

Fig. 2.6 Neural network with two parts for model modification

If the connection weight G between the model tuning and the process model is 1, it means stable process state because recipe equals real input. However the real input used on the process may be different from recipe by the abnormality. Table 2.1 shows the characteristics of the abnormality in each input [14].

Table 2.1 The characteristics of the tolerance of inputs

RF power (W)	Pressure (mtorr)	Gap (cm)	SF6 (sccm)	He (sccm)	Cl2 (sccm)
gain	gain	gain	offset	offset	offset

If input has gain, it changes the connection weight value of neuron between the model tuning and the process model. For example, if Rf power of recipe indicates 10 W and loaded Rf power is 20 W by abnormality, the process shift may occur. The shift needs the new modeling and new recipe, in which the connection weight G will be changed for the compensation the gain of Rf power.

Offset influences on the threshold of neuron in the model tuning. However, it is more efficient to control the threshold of hidden layer in the process model. Because input neurons are connected to all neurons of hidden layer in the process model, and in the course of new modeling, offset generates the change in the threshold of the each neuron in the process model as shown Eq. (2-6).

$$H = f\{W \cdot I + (W \cdot e + \delta)\} \qquad (2\text{-}6)$$

where H is the output of hidden layer, I the input, e the offset, and W, and δ the connection weight and threshold of hidden layer, respectively. Input error e in the neuron of hidden layer is multipied with W and add to the threshlod. As a result, for new modeling due to the process shift the connection weight in the model tuning and the threshold of hidden layer in the process model must be changed. It is noted that the connection weight in the process model needs no change.

Setup of new control input

If new modeling for com- pensation of the process shift is completed by the model modification, then we can select the new control input to recover the process output to the target.

3. Results

To evaluate the performance of the integrated process control system, Rainbow 4420 plasma etching equipment (Lam Research Corporation) was selected and programmed in the IBM PC 486. The integrated process control system in this study took focuses three points:

1) The predictive capability of plasma etching process modeling.
2) The generation of optimal recipe.
3) the compensation of the process shift.

3.1 Modeling

The RF power, pressure, electrode gap, and the flow of SF_6, He and Cl_2 are the control inputs and the etchrate of polysilicon is the process output. Table 3.1 shows the range and resolutions of input parameters.

Table 3.1 Control input and range

Control Input	Range	Resolution
RF power	200 - 400	1 (W)
pressure	200 - 550	1 (mtorr)
Electrode gap	0.7 - 0.9	0.1 (cm)
SF_6 flows	20 - 100	1 (sccm)
He flows	25 - 150	1 (sccm)
Cl_2 flows	15 - 150	1 (sccm)

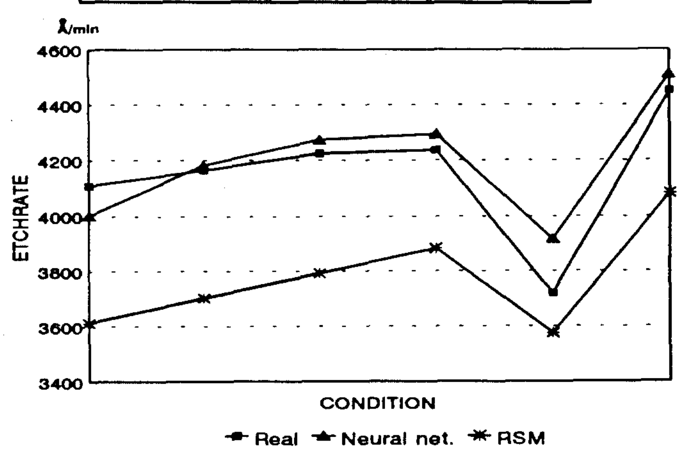

Fig. 3.1 The comparison of the etchrate with the statistical model

The ranges shown in Table 3.1 for the input and output data of plasma etching are obtained through 37 experiments. 31 of them are the learning data for modeling and the rest the estimation data. Fig. 3.1 shows the comparison of the predictive capability between the neural network model and the statistical model.

3.2 The Optimal Control Input Tracking

Table 3.2 shows the initial values of the genetic algorithm parameters used.

Table 3.2 The parameters of genetic algorithm

parameter	initial vlaue
generations	30000
populations	100
crossover rate	0.9
mutant rate	0.01

Target outputs for etch rate is 4000Å/mim and genetic algotirhm with the resolution of the Table 3.1 searched the optimal input in the range shown in Table 3.1. In Table 3.3, the optimal control input and Table 3.4 shows the target, model output and the real output by the control input in reference to Table 3.3

Table 3.3 Control input searched for target output

RF Power	pressure	Gap	SF_6	He	Cl_2
363	340	0.7	25	123	60

Table 3.4 Target, model, and real outputs

	Target	Real	Model
Etchrate	4000.0	4013.7	4005.6

3.3 The Compensation of The Process Shift

To estimate the compensation of the process shift, assignable causes in the course of run are requested. The input is then deliberately changed while recipe was maintained. Fig. 3.2 shows the control chart of the etchrate in the stable process state.

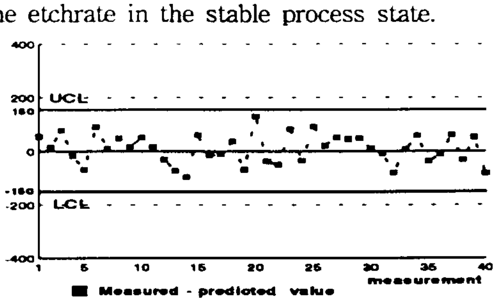

Fig. 3.2 The control chart of etch rate in the stable process state

Fig. 3.3 shows the control chart of etchrate when real RF power is 10w less than RF power of recipe. In Fig.3.3, it represents the stable output state until the 20th measurement and in the next alarm out of the range ocurred in the point 21. Through continuous points 22, 23, 24, it indicates that the process shift really occurred.

The 25th measurement shows that the process output could be recovered in the control limit as a result of process, which runs after selecting new control input in Feedback controller.

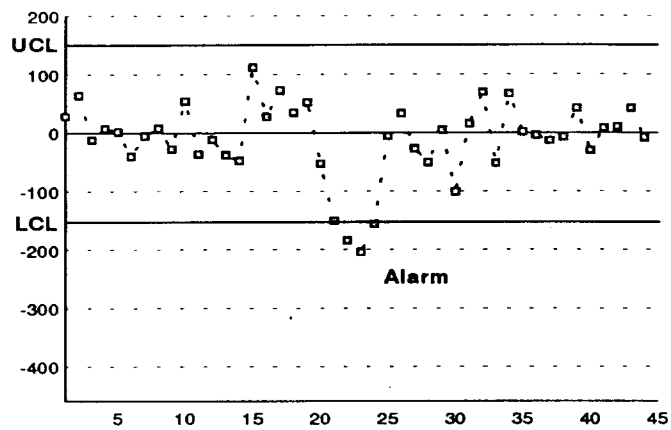

Fig. 3.3 Control chart of etchrate when Rf power is 10W less than that of recipe

Fig. 3.4 shows the responce of controller when real SF_6 flow is 10% less than that of recipe. As the same of Fig. 3.3, the abnormality of SF_6 flow occurres the process shift from point 21 to 24 and Feedback controller returns the etch rate into the control limits from 25th measurement.

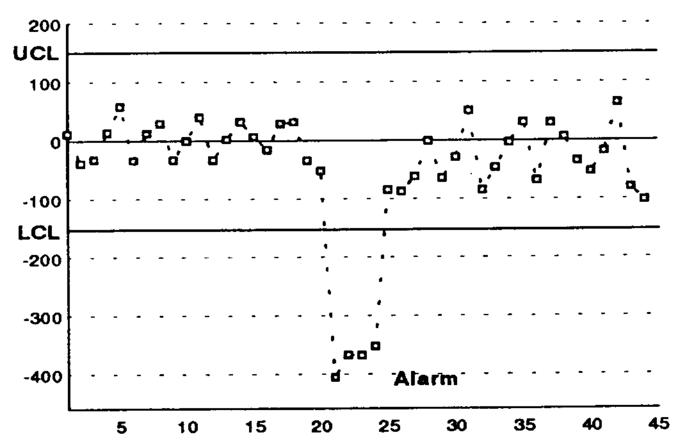

Fig. 3.4 Control chart of etchrate when SF_6 is 10% less than that of recipe

Next, the abnormality occurred in the plural inputs simultaneously. Fig. 3.5 is the control chart of the etch rate when RF power is 30W less and SF_6 is 10% less. Also, it shows that the process output are recovered into the limits when the plural abnormalities occurred simultaneously.

The above result enables us to estimate the control capability of our control system. In the Fig. 3.3~3.5 whenever the process shift occurred by abnormality, we confirmed that the compensation and control are possible by neural network model based statistic controller.

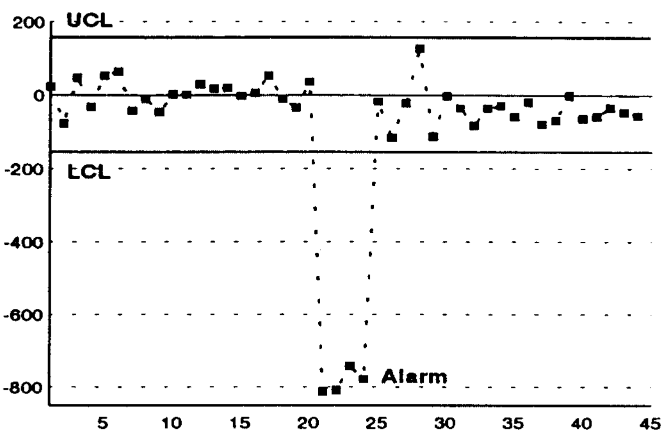

Fig. 3.5 Control chart of etchrate when Rf power is 30W less and SF_6 is 10% less

The objects of the process control system is to keep the process output on the optimal state and make the quality better. Accordingly The object of each controller module is the selection of the otpimal control input, the compensation of the process shift. In addition, how the process outputs keepup the target closely estimates the total capability of the intregrated process controll system as we mentioned.

4. Conclusion

The integrated process control system using neural network model based statistical process control is proposed. For modeling of the etch process, the proposed model is used, and for tracking of the optimal control, input is adopted from genetic algorithm. Also, feedback control recover the process output to the stable state. The multi layered neural network with two parts is designed to accomplish this. Integrated process control system has the following advantages. 1) Neural network model is more efficient and functional than statistical model. 2) Searching for optimal control input by genetic algorithm is very accurate. 3) Our system can compensate the process shift quickly and efficiently. 4) Integrated process control system makes the error between process output and target smaller with better quality. Control of the process for more efficient, the simple and reliable measurement of on-line data is needed in RAM product lines.

Reference

[1] Christopher D. Himmel and Gary S. May, "Advantages of plasma etch modeling using neural networks over statistical techniques", IEEE Trans. Semiconductor Manufacturing, vol 6, no 2, May 1993

[2] Byungwhan Kim and Gary S. May, "An optimal neural network process model for plasma etching", IEEE Trans. Semiconductor Manufacturing, vol. 7, no. 1, 1994

[3] Edward A. Rietman and Earl R. Lory, "Use of neural networks in modeling semiconductor manufacturing process : an example for plasma etch modeling", IEEE Trans. Semiconductor Manufacturing, vol 6, no 4, Nov 1993

[4] Paul E. Riley and David A. Hanson, "Study of etch rate characteristics of SF_6 / He plasma by response-surface methodology : effects of interelectrode spacing.", IEEE Trans. Semiconductor Manufacturing, vol. 2, no. 4, Nov 1989

[5] S. S. Han, M. Ceiler, S. A. Bidstrup, P. Kohl and G. May, "Modeling the properties of PECVD silicon dioxide films using optimized back-propagation neural networks", IEEE Trans. Component, Packing and Manufacturing Technology, vol. 17, no. 2, Jan 1994

[6] Gary S. May, Jiahua Hwang and Costas J. Spanos, "Statistical experimental design in plasma etch modeling", IEEE Trans. Semiconductor Manufacturing, vol. 4, no. 2, May 1991

[7] John J. Grefenstette, "Optimization of control parameters for genetic algorithms", IEEE Trans. Systems, Man, and Cybernetics, pp 122-p128, Jan 1986

[8] Jacques de Villiers and Etienne Barnard, "Backpropagation neural nets with one and two hidden layers", IEEE Trans. Neural Networks, vol 4, no 1, Jan 1993

[9] Goldberg, "Genetic algorithms in search, optimization and machine learning", Addison Wesley, 1989

[10] Bart Kosko, "Neural networks and fuzzy systems", Prentice-Hall, 1992

[11] S. M. SZE, "VLSI Technology", 2nd Edit., McGRAW-HILL, 1988

[12] Lam Rearch, "Rainbow 4420 manual operation and maintenance", vol. 1, 1992

[13] P.K.Mozumder and G.G.Barna, "Statistical feedback control of a plasma etch process", IEEE Trans. Semiconductor Manufacturing.

[14] P.K.Mozumder and Sharad Saxena, "A monitor wafer based controller for semiconductor process" IEEE Trans. Semiconductor Manufacturing, vol 7, no 3. Augst 1994.
[15] Cotas J.Spanos, Hai-Fang Guo, "Real-Time Statistical Process Control Using Tool Data." IEEE Trans. Semiconductor Manufacturing, pp. 308-318 Nov. 1992.
[16] J. Bert Keats and Norma Faris Hubele. "Statistical Process Control in Automated Maufacturing." New York and Basel, 1990.