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A NOVEL PROCESS MONITORING AND CONTROL SYSTEM BASED ON A NEURAL MANUFACTURING CONCEPT

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Summary

This paper describes our work to produce "smart" equipment using a neural network to provide intelligence for process monitoring, adaptive control, metrology, and equipment diagnostics. This novel system will improve both quality and yield for critical thin films used in semiconductors, superconductors, high-density magnetic and optical storage, and advanced displays, all of which are critical to maintaining our leadership in the multibillion-dollar electronics and computer industries. The equipment will have on-line, real-time diagnostics capabilities to detect component problems early in order to minimize maintenance and downtime.

Introduction

U. S. integrated circuit (IC) manufacturers have relied on highly innovative R&D technology advances to remain competitive. Unfortunately, the science and technology of basic manufacturing processes did not receive the same R&D effort, resulting in a decline in U. S. manufacturing capabilities. The 1992 National Advisory Committee on Semiconductors Report[1] stated that the condition of U.S. high-technology companies has not improved. The share of the world market held by U.S. electronics manufacturers fell 14% from 1985 to 1990, representing $100 billion in lost revenues.

U.S. IC manufacturers are now using a mixture of old and new manufacturing methodologies. Some of the associated problems are: 1) Although existing process control is a closed-loop system, it is not a direct closed-loop control of the fabrication process itself. Instead it is a collection of individual closed-loop controls of peripheral parameters such as pressure and gas flow. This type of control is indirect, since it is not the measured variables that individually control the outcomes of a process, but the synergistic effect of all the parameters that governs the results. 2) If a process deviates from specifications during processing, the process engineer has very few options to "rescue" a bad run. 3) At present, processing errors are corrected by "rework" or "processing feed-forward." Scheduling such reprocessing runs with "fresh" runs is a logistical problem. 4) The cluster tool concept must be extended to include metrology. This complicates the cluster integration. 5) Diagnosing equipment problems only after the equipment is down is highly inefficient.

We believe that any attempt to solve the U.S. manufacturing problems should involve some form of equipment intelligence based on artificial neural networks[2, 3] and fuzzy logic. We call the application of human-like intelligence to manufacturing "neural manufacturing."

Approach

For a plasma-based processing system, plasma information is obtained in the form of spectra from optical sensors. We propose to use an artificial neural network to monitor and analyze these spectra; the outputs of the artificial neural network will represent information corresponding to the processing inputs for the system, such as gas flow, rf power, and pressure. With this *in-situ* real-time information pertaining to the plasma just above the wafers, adaptive process control is then achieved by using this information to make corresponding corrections at the level of the slave controllers (Fig. 1).

There are numerous advantages in using an optical sensor. First, highly reliable optical sensing techniques (e.g., optical spectrometers[4]) are available and are routinely used in semiconductor processing. Second, optical sensors can be external and thus do not perturb the process. Third, optical sensing is extremely fast, which is an important consideration for single-wafer processing and thus allows real-time monitoring and control. As a result, one can concentrate on using neural networks to interpret signals from plasma, because there should be a one-to-one correspondence between the plasma and the input conditions (e.g., gas flow, pressure). This approach is advantageous in the sense that the wafer "sees" the plasma, which is the synergistic effect of all input conditions and not just individual pressures or gas flow rates. If, for example, one of the flow controllers is off in terms of calibration, it may then be maintaining a wrong flow condition and yet reports back that its flow is at the target value. Under the same conditions, the plasma spectrum will be different. The problem of such a novel approach is that differences in the plasma spectra are very subtle. We have demonstrated that the problem of interpreting very subtle signals from a very noisy environment such as plasma can be solved by using neural networks for data analysis and interpretation. Our neural network simulations detect subtle differences that a process engineer or even a plasma specialist cannot see.

Although we believe that this novel concept can affect a wide spectrum of manufacturing, we are particularly interested in applying this approach to backend plasma processing, because the backend interconnects strongly influence chip yield, performance, and reliability. Also, applying neural manufacturing to the backend inter-chip-level interconnects will impact the critical packaging technology, which dictates system performance. Backend processing also benefits both silicon-based and III-V or II-VI based processing. Once this project is successfully demonstrated, the proven principles can be applied to other types of semiconductor equipment and processing and manufacturing in general.

Experiments and Results

For a demonstration of the above approach, we selected an oxide reactive-ion-etching (RIE) process. Experiments were performed in a batch-type parallel-plate reactor processing seven wafers per run. In order to understand the limitation of our approach, we selected a process with extensive polymerization and a set of processing conditions representing a very large processing space (Tables 1 and 2). The four processing inputs are operational pressure, rf power, CHF_3 gas flow, and H_2 gas flow. We have chosen a center cubic experimental design[5] (Fig. 2) and thus minimize the number of experiments to cover a very large 4-dimensional operating space. A total of 30 experiments were performed with 6 repeated experiments. Data collected from these 30 experiments were used for the training of the neural networks. Additional experiments were performed to test the performance of the network.

A diode array optical spectrometer with 1024 optical channels was used to monitor the plasma. Because of the grating used, only 731 of the 1024 optical channels are active. The wavelength resolution of the system is 0.59 nm, covering a spectral range from ~320 to ~740 nm. Plasma spectrum distortion due to extremely heavy polymerization from a high amount of hydrogen was seen (Fig. 3). This distortion was partially removed by preprocessing, resulting in plasma spectra that appear almost identical (Fig. 4) even though the processing input conditions are very different. Our computer-simulated neural network uses 743 neurons. A three-layer neural network (Fig. 5) was designed to distinguish the subtle differences between the inherently noisy plasma spectra and to identify the corresponding variations in processing conditions. The four outputs of the network represent the flows of each of the gases, the pressure and the power for the system correspond to the plasma.

The resulting network can accurately quantify the processing conditions for which it is trained with a maximum of 0.33% rms error (Table 3). Furthermore, it predicts the processing conditions reasonably well from "unseen" plasma spectra generated by the test experiments.

Discussion

The network learns on its own from the training data and selects the most pertinent channels to look at without any guidance from human experts and without needing any explicit or implicit plasma diagnostics rules. For example, when hydrogen gas flow alone was allowed to vary, the network - after training - by itself identified the correct channels to monitor this flow change. This self-learning capability represents a fundamental difference between neural networks and other "intelligent" systems. This capability is significant because the processing engineer may actually learn from the network and gain a better understanding of the plasma. In addition, as more data are available, such a system may behave more and more intelligently.

Process control will be achieved when the neural network identifies any plasma deviation and subsequently sends correction signals to the slave controllers (e.g., pressure controller). In neural manufacturing, mistakes are prevented during processing by this adaptive control. This real-time control prevents mistakes by correcting the process in real time so that the results satisfy the target criteria. Thus, the amounts of "rework" and "feedforward" can be minimized. This approach is especially significant for the cluster tool design, because if the process satisfies the target criteria, then most metrology equipment may be unnecessary. In addition, if we can predict an equipment problem ahead of time and fix it just in time, then we can minimize maintenance and maximize uptime and performance. In our case, by examining the magnitude of the correction signals sent by the neural controller we can intelligently decide when actual servicing is needed and which component needs to be replaced. Thus neural manufacturing impacts not only processing but also maintenance, which is a vital factor in the manufacturing cost equation.

Performance, cost, and space requirements must be considered for implementing this type of neural controller. We are currently developing a 96-neuron cascadeable neural network VLSI chip[6] that can be used to implement the above process monitor/control system. This chip is expected to run at 12 billion interconnects/sec and thus should achieve real-time monitoring and control. We estimate the cost of such a neural network chip will be on the order of a few hundred dollars. As a result, this is an extremely cost effective way to boost the performance of processing equipment that typically costs a few million dollars. In addition, cleanroom space is costly. Our small controller will be tucked away in the equipment without affecting the footprint of the equipment itself or the cleanroom space.

Conclusions

We have demonstrated one aspect of "neural manufacturing," an intelligent manufacturing concept. This approach based on neural networks would improve yield by improving real-time process control and minimize downtime by predicting component failure ahead of time. We have successfully demonstrated the monitoring capability of this concept in a plasma-based reactive-ion etching system by extracting correct input processing conditions from the optical spectra emitted by the plasma.

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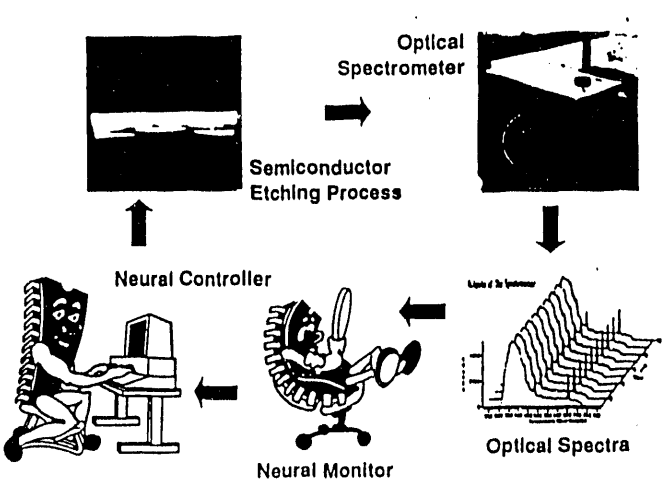

Fig. 1. Plasma process control using neural networks. Information from optical spectra is used to correct the etching process.

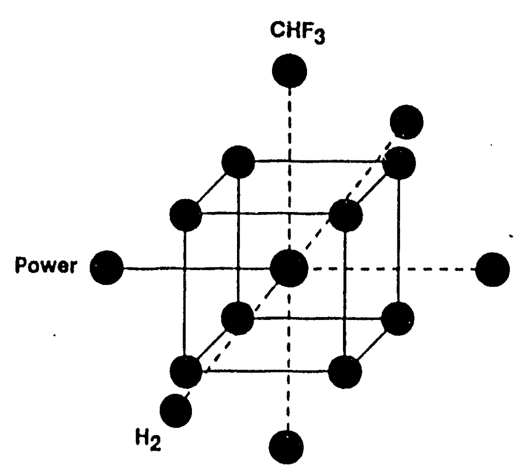

Fig. 2. Training data generated by center cubic experimental design. This design covers a very large operating space with relatively few experiments.

Table 1. Input conditions for our RIE experiment.

Input Parameter	Range
H_2 gas flow	0.0 - 4.0 sccm
CHF_3 gas flow	70 - 110 sccm
Power	400 - 800 Watts
Pressure	50 - 70 mTorr

Table 2. Output parameters measured for our RIE experiment.

Output Parameter	Range
Oxide Etch Rate	-45 - 800 Å/min
a-Si Etch Rate	-5 - 60 Å/min
Etch Selectivity	7 - 35

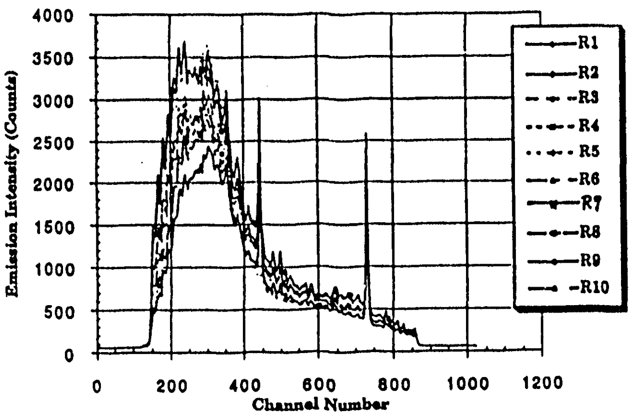

Fig. 3. Optical emission spectra for ten runs. The spectrum distortion is due to polymerization from H_2.

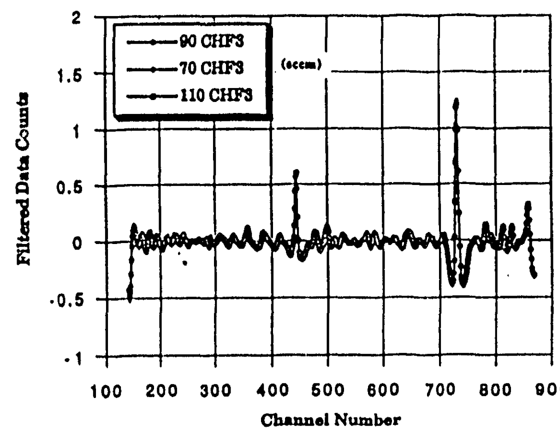

Fig. 4. Comparison of preprocessed plasma spectra with various amounts of CHF_3 after preprocessing. Neural networks can distinguish the subtle differences in these spectra.

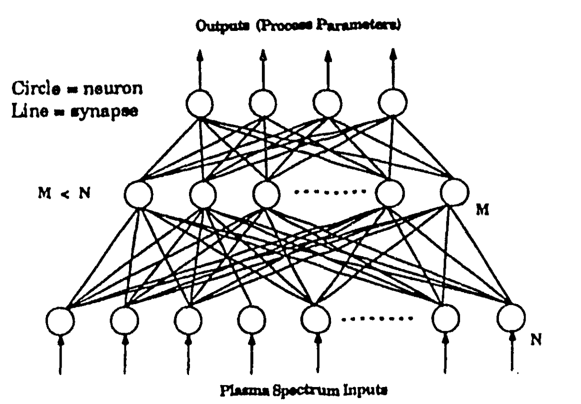

Fig. 5. A three-layer neural network model. The outputs represent the processing input parameters.

Table 3. Summary of the neural network results. The RMS deviation is from the comparison between neural network results and trained data.

Parameter	RMS Deviation
H_2 gas flow	0.29 %
CHF_3 gas flow	0.19 %
Power	0.33 %
Pressure	0.25 %

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