퍼지 및 지능시스템학회 논문지 2004, Vol. 14, No. 4, pp. 390-395

데이터 마이닝과 지능 모델링에 기반한 에칭공정의 공정관리시스템 설계

Design of Process Management System based on Data Mining and Artificial Modelling for the Etching Process

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요 약

반도체 공정은 많은 단위 공정으로 이루어진 복잡하고 동적인 공정이다. 그 중 에칭공정은 반도체 생산에서 중요한 공정 중 하나이다. 본 논문에서는 데이터 마이닝과 지식 획득을 통한 의사지원시스템으로 생산성과 수율을 높일 수 있는 시스템을 구성하고자 하였다. 제안된 방법은 퍼지 논리와 신경망으로 구성되는데, 신경망으로 에칭공정의 품질을 나타내는 품질에 대한 결과를 예측하고, 예측된 결과를 퍼지 추론 시스템으로 분류하는 과정으로 수행된다. 퍼지 논리에 사용된 규칙은 전문가의 지식에 기반하여 도출되거나 데이터로부터 도출된다. 본 시스템을 통해 공정의 최적 조건을 찾아 효율을 높이는 것이 본 연구의 주요 목표이다.

Abstract

A semiconductor manufacturing process is the complicate and dynamic process, and consists of many sub-processes. An etching process is the most important process in the semiconductor fabrication. In this paper, the decision support system based upon data mining and knowledge discovery is an important factor to improve the productivity and yield. The proposed decision support system consists of a neural network model and an inference system based on fuzzy logic. Firstly, the product results are predicted by the neural network model constructed by the product patterns that represent the quality of the etching process. And the product patters are classified by expert's knowledge. Finally, the product conditions are estimated by the fuzzy inference system using the rules extracted from the classified patterns. Prediction of product qualities can be linked to each input and process variables. We employ data mining and intelligent techniques to find the best condition of the etching process. The proposed decision support system is efficient and easy to be implemented for the process management based upon expert's knowledge.

Key words : Neural network, fuzzy logic, decision support system, data mining

1. Introduction

The artificial intelligence is an algorithm that systematizes expert's accumulative knowledge and experience in the specific field and will use when required. Where, the terminology called knowledge can be used separately or together with information. Definitely saying in the viewpoint of data, the information is an outcome of the data processing and the knowledge is accumulative know-how through the systematic use of information [1]. Information can becomes a source of competitive power as itself, but if information can be developed to knowledge, the competitive power should be strengthened more. Competition between corporations is deepening, so awareness of the importance of information is spreading. But it is very important to extract useful information from a large amount of data. It is the concept of data mining that is shown in this need [2].

The data mining is a work that extracts relevant information from a large amount of data using automatic and intelligent techniques and utilizes in decision-making. The network between manufacturing systems is constructed for the operation of production planning and maintenance of production equipments that uses the information-based system with data mining. This information-based system can flexibly cope with the change of actual production or operation conditions by more efficient product scheduling and maintenance of manufacturing equipments. The main goal of the

접수일자 : 2004년 5월 27일
완료일자 : 2004년 6월 28일
감사의 글 : 본 연구는 산업자원부(생산기술연구원) 프로젝트에 의해 일부 지원 받았습니다.

algorithms is to analyze the manufacturing process and operation status rapidly and to make a decision easily in this situation.

In past decades, the clustering method [3], input space partition [4], neuro-fuzzy modeling [5], and neural network [6] and others have been researched in the major categories of rule extraction and data modeling. Knowledge extraction is the most important part of the intelligence that has been developed much for past decades. Neuro-fuzzy was introduced at early 1990s; it is an important method to generate rules. For rule generation, clustering [7] and input space partition method were also applied much in the several parts. And the extension matrix [8], high order division [9], decision tree [10] and others were studied for information extraction. The concept of the input space partition method was to classify the input space by conditional space partitions, so this method reflects expert's knowledge. In this paper, the neural networks and fuzzy logic were respectively applied to design models and to extract rules for the decision support system of the process operation.

2. Methods

2.1 Etching Process

An etching process is a very important unit process of semi-conduct processes. The etching process is a chemical process that puts the slices in the chemical solution and makes reaction with the solution to shorten thickness of slice, or to remove surface defects or surface stress. The etching technologies are broadly separated by dry and wet etching methods. The simulation data of dry etching is employed in this research.

Fig. 1 shows the schematic diagram of the decision support system that analyzes the process status using data mining and knowledge discovery steps that are called as the data model and inference system. Sensors or measuring instruments for self-diagnosis are not attached in most of equipments assembled in physical processes. Therefore, it is not easy to diagnose the process and

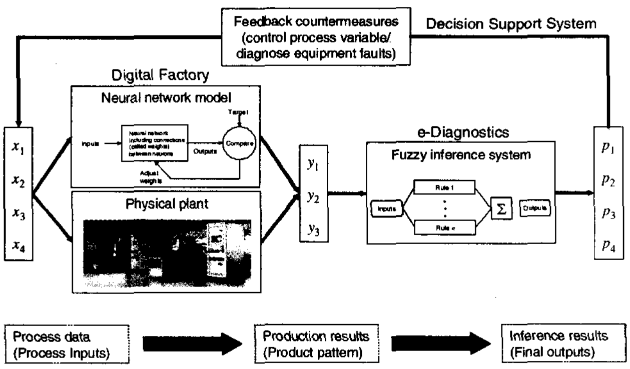


Fig. 1. Proposed process management system.

equipments with direct detection of equipments. This paper proposes the indirect diagnosis method to detect the process equipments considering process status and product results. Whether product qualities are affected by equipments actions under several conditions can be examined by comparing the product pattern corresponding to each process input.

2.2 Neural Network

Neural networks are computer algorithms inspired by the way information is processed in the nervous system. An important difference between neural networks and standard IT solutions is their ability to learn. This learning property has yielded a new generation of algorithms that can [11]

- learn from the past to predict the future,
- extract rules for reasoning in complex environments,
- and offer solutions when explicit algorithms and models are unavailable or cumbersome.

Based on these principles, neural networks have yielded many successful applications, in branches as diverse as finance, retail and logistics, medicine and health, marketing, fabrication and industrial control, and energy and utility.

The main advantages of neural networks stem from their ability to recognize patterns in data. This can be achieved without a priori knowledge of causal relationships, as would be necessary in knowledge-based systems. Their applications include classification, forecasting, and modeling. In this research, it is difficult to perform the total inspection in the physical manufacturing line of the semiconductor, so the neural network model is employed to cover the weak points with simulation.

2.3 Fuzzy Logic

Fuzzy Logic is a departure from classical two-valued sets and logic that uses soft linguistic system variables and a continuous range of true values in the interval, rather than strict binary decisions and assignments. Formally, fuzzy logic is a structured, model-free estimator that approximates a function through linguistic input/output associations.

Fuzzy rule-based systems apply these methods to solve many types of real-world problems, especially where a system is difficult to model, is controlled by a human operator or expert, or where ambiguity or vagueness is common. A typical fuzzy system consists of a rule base, membership functions, and an inference procedure (see Fig. 2). Some fuzzy logic applications include control, information systems, pattern recognition, and decision support. The key benefits of fuzzy design can [12]

- simplify & reduce development cycle,
- be ease of implementation,

• and provide more "user-friendly" and efficient erformance.

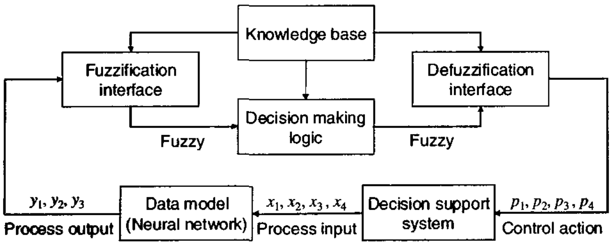


Fig. 2. Basic procedure of fuzzy inference system.

3. Experimental Results

The final goal of this research is to design a data model for a simulator of the manufacturing process and to build a process management system as shown in Fig. 3. The algorithm consists of 5 steps that include the input, pre-processing, data modelling, inference system construction and output stage. The data model and inference system are main algorithm in the processes. Neural networks and fuzzy logic were applied to design the proposed model and inference system.

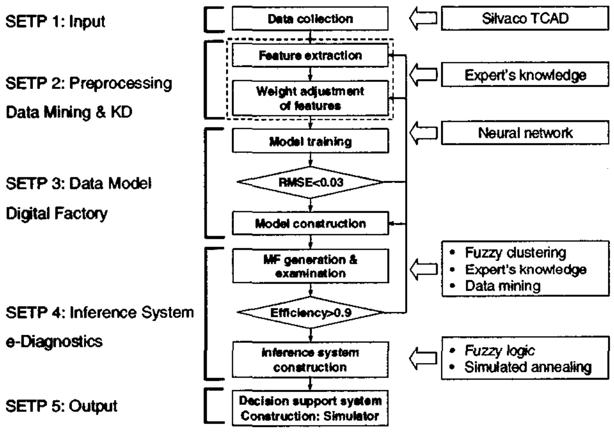


Fig. 3. Total process of the decision support system.

3.1 Step 1: Input

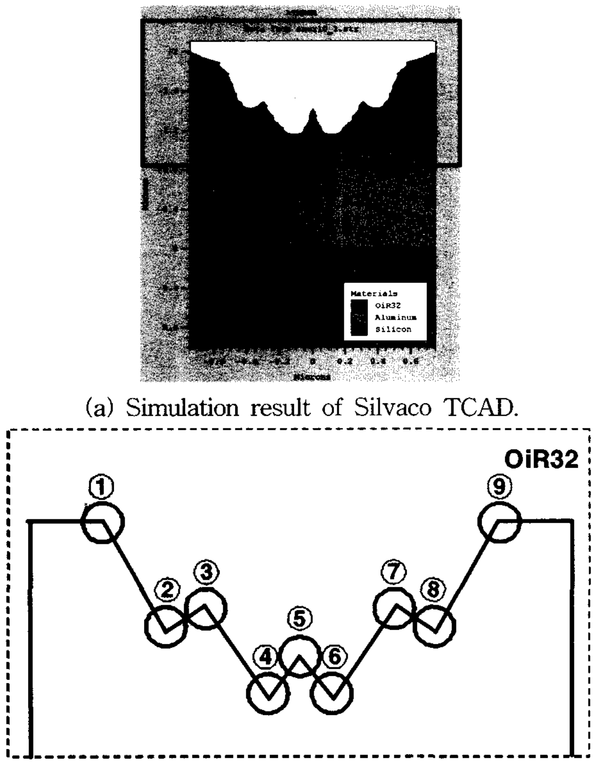
Test data are generated by the commercial simulator (TCAD) that was used as a substitute of physical plants. The upper layer (Oir32) is control target of the etching process. Input variables of the etching process consist of Bake Time, Bake Temp, Circle Sigma, and Projection na. The etching status of Oir32 is determined by the four input variables. Ranges of variables are decided by the Taguchi method that is an optimization method of the experiment design. Firstly, maximum and minimum ranges of each variable are defined and the range values (discrete ranges) are determined as shown in Table 1. This method can reduce a number of experiments and improve the efficiency. 36 test data sets are collected corresponding to the inputs.

Table 1. Input variables for data generation.

Input	Variables	Range	Values
$x1$	Bake Time	2	1(30) 2(60)
$x2$	Bake Temp	2	1(125) 2(185)
$x3$	Circle Sigma	3	1(0.3) 2(0.5) 3(1.0)
$x4$	Projection na.	3	1(0.28) 2(0.4) 3(0.52)

3.2 Step 2: Pre-processing

9 numbers of feature points are extracted from approximated picture as shown in Fig. 4. The depth of the 4th feature point, difference between the 4th feature and the 5th feature, and gradients between the 2nd feature and the 3rd feature are y1, y2 and y3 product variables, respectively that express the product quality. Thus, inputs variables are four from x1 to x4 and product variables are three from y1 to y3.as shown in Table 2.



(a) Simulation result of Silvaco TCAD.

(b) Extract feature points from data.

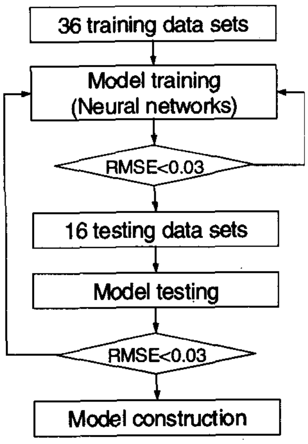
Fig. 4. Feature points of Oir32.

Table 2. Product variables of plant.

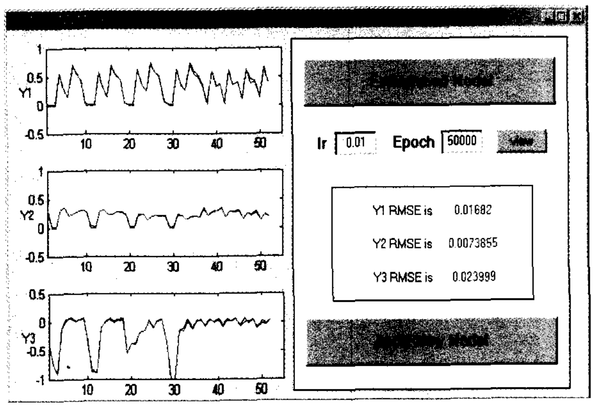
Var	Description of variables
$y1$	Etching depth at the initial point (Depth of 4)
$y2$	High of the centre point (Difference between 4 and 5)
$y3$	Slope of left side (Gradient between 2 and 3)

3.3 Step 3: Construction of Data Model

In this paper, the neural network modelling technique was employed to design the data model for matching input variables (x1 to x4) with product variables (y1 to y3) as shown in Fig 5.



(a) Flowchart of the Step 3.



(b) application of neural network simulator.

Fig. 5. Flowchart of the step 3 and application window.

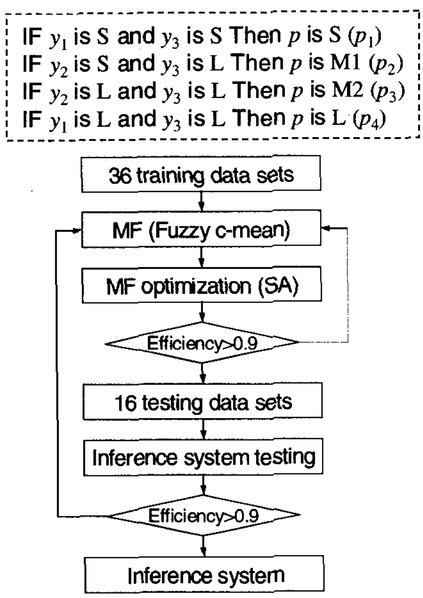
Table 3. Prediction results of product variables.

No.	Target values			Prediction results		
	y_1	y_2	y_3	y_1	y_2	y_3
1	0.359	0.343	-0.069	0.330	0.330	-0.065
2	0.005	0.210	0.022	0.024	0.209	0.045
3	0.597	0.285	0.015	0.598	0.274	-0.001
4	0.330	0.292	0.065	0.343	0.297	0.046
5	0.363	0.343	-0.055	0.351	0.321	-0.084
6	0.013	0.179	0.038	0.018	0.185	0.013
7	0.603	0.273	0.007	0.599	0.267	0.007
8	0.344	0.257	0.061	0.334	0.272	0.036
9	0.398	0.281	-0.076	0.398	0.283	-0.053
10	0.088	0.141	-0.005	0.091	0.139	0.052
11	0.625	0.238	0.004	0.614	0.235	-0.026
12	0.390	0.202	0.037	0.463	0.225	0.040
13	0.340	0.260	-0.093	0.429	0.284	-0.109
14	0.121	0.131	0.014	0.134	0.130	-0.022
15	0.630	0.229	-0.019	0.659	0.221	-0.036
16	0.388	0.188	0.038	0.386	0.172	0.042
RMSE				0.025	0.012	0.025

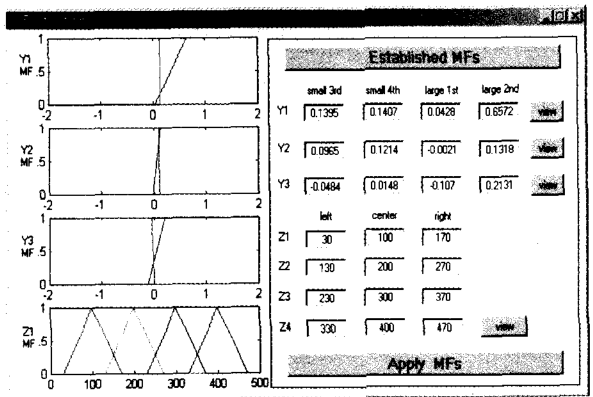
As considering the traditional mathematical model, it is very difficult to identify the process status in nonlinear and complex systems. But the neural network is a very effective modelling method to express the relationship between inputs and outputs of complicated systems. Therefore, 36 data sets for input variables and product variables were trained by the neural network model. The number of layers was four and the number of nodes was 7, 9, and 11, respectively. The learning rate was 0.01 and the epoch was 50,000 iterations. And the back-propagation algorithm was employed for model learning. The model was trained until the RMSE became under 0.03. Table 3 shows the prediction results of the product features using the neural network model. The prediction performance is good enough to be applied in the estimation of product qualities.

3.4 Step 4: Construction of Inference System

In this paper, the fuzzy inference system is applied to estimate the patterns of the product outputs. The inference rules were extracted by the results of model estimation. This inference system was the primary step to support a decision of the system operation (see Fig. 6).



(a) Flowchart of the Step 4.



(b) application of the fuzzy inference system.

Fig. 6. Flowchart of the step 4 and application window.

The rules were generated by fuzzy c-mean that is one of efficient data mining methods. The number of clusters was determined by experts considering input variables (x1 to x4) and product patterns (y1 to y3) that can lead final results (p1 to p4). The expert should play an important role in making a decision whether the product is normal or not with checking the product qualities. The fuzzy inference system was built by 36 data sets that were employed in the step of model construction. And 16 test data were used for validation of the inference performance. Table 3 shows the classification results based on the fuzzy inference system. As considering the accuracy, the classification accuracy is 93.75%. The membership functions were optimized by the simulated annealing that is one of fast optimization methods. The optimization was repeated until the performance was achieved over 90% accuracy. 8 rules were initially generated but final rules were reduced by 4 rules for efficiency of the inference system as follows;

Table 3. Classification results of product patterns.

No.	y_1	y_2	y_3	Target	Result	Range	Pattern
1	0.359	0.343	-0.069	4	3.52	3.5≤p<4.5	4
2	0.005	0.210	0.022	3	2.52	2.5≤p<3.5	3
3	0.597	0.285	0.015	3	2.96	2.5≤p<3.5	3
4	0.330	0.292	0.065	3	2.52	2.5≤p<3.5	3
5	0.363	0.343	-0.055	4	3.71	3.5≤p<4.5	4
6	0.013	0.179	0.038	2	2.47	1.5≤p<2.5	2
7	0.603	0.273	0.007	3	2.74	2.5≤p<3.5	3
8	0.344	0.257	0.061	3	2.52	2.5≤p<3.5	3
9	0.398	0.281	-0.076	4	3.51	3.5≤p<4.5	4
[redacted]							
11	0.625	0.238	0.004	3	3.41	2.5≤p<3.5	3
12	0.380	0.202	0.037	3	2.52	2.5≤p<3.5	3
13	0.406	0.260	-0.093	4	4	3.5≤p<4.5	4
14	0.121	0.131	0.014	2	1.94	1.5≤p<2.5	2
15	0.630	0.229	-0.019	4	3.53	3.5≤p<4.5	4
16	0.388	0.188	0.038	3	2.52	2.5≤p<3.5	3
Accuracy corresponding to the inputs							93.75%

3.5 Step 5: Output

The main goal of this research is to develop the process management system that consists of a process simulator and a product inference system. The final proposed system can diagnose the abnormal situations of process status and adjust the unexpected plant conditions into normal situations. In this step, the guide of the management and the control command of the process will be drawn to manage the manufacturing plant effectively and stably.

The process simulator and diagnostics were developed to handle the processes and equipments using neural networks and fuzzy logic. This integrated system can make a decision for the process and equipment management. Table 4 provides the control command and operating guide based on the results of the fuzzy inference system when faults happen.

Table 4. Control and diagnosis action to outputs.

Output patterns	Control command and diagnosis action
$p1$ (pattern 1)	• Decrease $x1$ • Check baking heater or heating controller
$p2$ (pattern 2)	• Increase $x3$ • Check coater or coating controller
$p3$ (pattern 3)	• Good product
$p4$ (pattern 4)	• Decrease $x1$ or/and Increase $x4$ • Check baking heater or heating controller and coater or coating controller

4. Simulation Results

Fig. 7 is the main control window of the designed simulator. By using this simulator, the production results can be estimated and the product pattern can be inferred at once. Also the incorrect results of prediction or inference are adjusted by re-organization and re-training of neural networks and fuzzy inference system. Fig. 8 shows an inferior product case that is inferred as pattern 4 case. In this case, the bake time has to be reduced and the projection na should be increased gradually. Fig. 9 shows the simulation result of the pattern 3 that is a good quality. Therefore, there are no control commands or management actions. This is the final goal of the process. Both the simulations were performed by arbitrary inputs $x1$ to $x4$ for analysis of products.

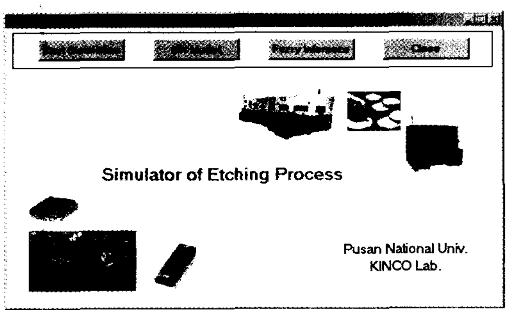


Fig. 7. Initial window of the built simulator.

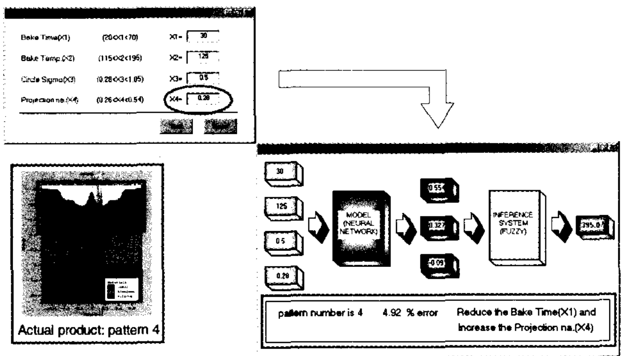


Fig. 8. The simulation result of the pattern 4.

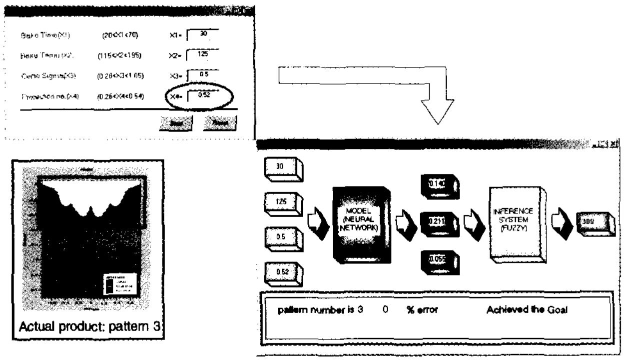


Fig. 9. The simulation result of the pattern 3.

5. Conclusions

The manufacturing process is the complex and dynamic system and this fabrication line contains other unit processes. The faults or breakdowns of the process can happen under the abnormal conditions that influence the product qualities or the production yields. The faults of process usually appear after the specific symptom than come out suddenly. In past decades, many techniques have been studied to solve these problems using artificial intelligence and data mining. In the past researches, model-based, case-based, and knowledge-based diagnosis methods were usually employed. Because each method has strong points and weak points the suitable method has to be selected according to the feature of the target system. And the combined technique can be more efficient than a single method. In this paper, the prediction model based upon neural networks is applied to estimate the special quality of products that are produced under the present input conditions. The final decision support system is built by using the fuzzy inference system that contains the reasoning functions for results of products.

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