LOGIC Product Yield Analysis by Wafer Bin Map Pattern Recognition Supervised Neural Network

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*Abstract –Wafer **Bin** Maps (**WBMs**) are important for yield improvement to trace root causes. The characteristic of WBMs patterns are formed by processes, so process engineers can collect clues from the patterns and correlate them with specific processes, and this can save much time and efforts in finding the root causes. However, the existing learning algorithms have the main shortage of product dependency. For this reason, this work adopted a supervised learning methodology to develop an on-line WBMs pattern recognition system that maps WBMs into 70x70 binary images to solve this issue. Furthermore, this work also proposed a learning scheme to recognize repeating failures that are usually viewed as random pattern in the existing approaches.*

INTRODUCTION

High yield is one of the most important core competences in the modern IC fabrication industries. Every semiconductor manufacturing company pays efforts on reducing variations and improving yield by monitoring and controlling the processes (Mirza et al. 1995)[2]. Wafer circuit probing(CP) is a functional testing after manufacturing processes. Every die will be categorized into one bin code after probing test. The output results of CP are so-called wafer bin maps(WBMs) and are important for yield improvement. Yield loss mechanism was proposed to identity the different sources of yield loss (Stamenkovic et al. 1996)[7]. This mechanism prioritized the improvement actions for engineers. Spatial patterns of WBMs are typical sources of systematic yield losses and this work will focus on reducing this kind of yield loss. The spatial patterns of **WBMs** are important hints for yield improvement, that's the reason why it is very important to quickly, efficiently and automatically detect critical patterns in practical applications.

The techniques of the existing approaches to detect WBMs patterns can be classified into two categories, i.e., statistical methods and machine learning methods.

Statistical Methods

Kaempf(1995)[1] presented a statistical-based method to analyze the WBMs cluster pattern in two-dimensional space. Similar approach adopted a binomial test by Kaempf(1995)[1] to determine the dies spatial distributions on WBMs. Mriza et al. (1995)[2] divided patterns into gross and local types to proposed ways to distinguish these two types. Gross failure type is a systematic type that means large amounts of dies are failed and may be caused by process or equipments variations. Local failure type is a random type that means few dies are failed and may be caused by in-line random particles. They applied Gibbs/Markov random field model to develop a test methodology, which can distinguish gross and local failures on WBMs. Friedman et al. (1997)[3] presented a two-stage spatial signature analysis method. In the first stage, defect images (good/bad, white/black, 0/1) are applied with morphological operation by 3x3 or 5x5 neighborhoods to smoothen the image. Then a threshold value must be determined for the spatial test model. The main limitation of statistical methods is that they can only detect whether there exists systematic patterns or not. They lack the capability to identify the detailed pattern type. This solution cannot provide more useful information for advanced root cause finding.

Machine Learning Methods

Lin(1998)[4] applied supervised neural network architecture to recognize systematic patterns. The main limitation of his research is that it is not capable of detecting repeating failure pattern that may be caused by lithography process or tester. Liu, et. al., (2002)[5] applied unsupervised neural network ART1 learning scheme to classify the patterns and if no similar patterns exist, a new pattern will be generated. A similar approach presented by Chien(2002)[6], which used Odds Ratio test to detect if there exists a systematic pattern, then applied ART1 to classify the patterns. In practical use in foundry fabrications, those approaches will encounter two problems. The first one is that there usually exist few critical patterns, too many derived-patterns could make engineers confused. The second one is the proposed training algorithm is product-dependent and therefore is hard to be implemented because there are too many products in foundry FABs. This work intends to develop an intelligent learning framework for WBMs pattern recognition to solve the limitations of the above methods. The proposed framework can detect four critical patterns, i.e., center failure, edge failure, local failure and repeating failure (see figure 1). These four patterns have critical impact on LOGIC product yield.

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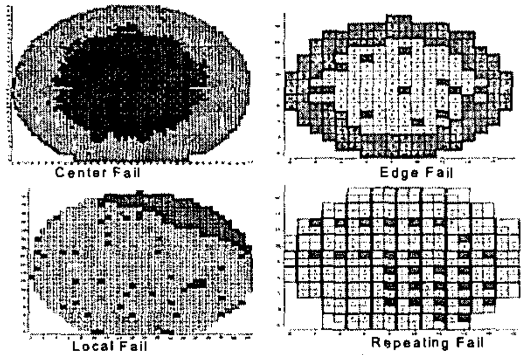


Figure 1 Typical failure patterns of wafer bin maps

METHODOLOGY

Spatial analysis of WBMs is important to yield enhancement. Figure 2 shows that the WBMs pattern recognition system developed in this work is a subsystem of **E**ngineering **D**ata **A**nalysis **S**ystem **(EDAS)** and it generates useful information for advanced correlation analysis to find the root causes. Figure 3 shows the WBMs pattern recognition architecture. Specific patterned samples are selected as the inputs of sample generator, which will divide, selected samples into training samples and testing samples. Then WBMs preprocess will transform WBMs into binary images for features extraction.

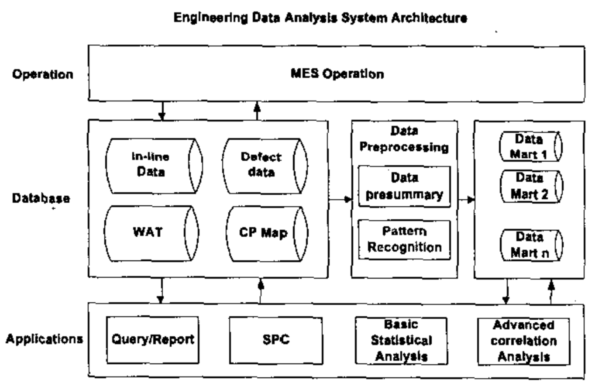


Figure 2 EDAS architecture

The research structure consists of four parts: critical patterns definition, data normalization, features extraction, models training and verification. They are described as follows:

Critical patterns definition

There might exist a lot of pattern types on WBMs, but only few types are critical that have major impact on yield. After collecting and summarizing the information from engineers, four major pattern types as depicted in figure 1 were defined. The first one is the center failure that might be caused by etching or CMP processes. The second is the edge failure that might be caused by etching process. The third is local failure that might be derived from process or equipment excursions. The last one is a repeating failure that can almost be derived from lithography process or probe testing equipment. This work intends to develop the pattern recognition to detect these four patterns systematically and automatically.

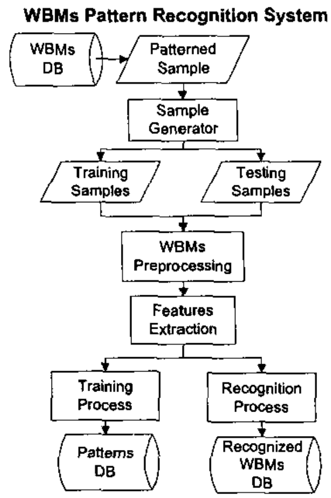


Figure 3 WBMs pattern recognition architecture

Data normalization

As mentioned above, the learning scheme is dependent with product for most of the existing approaches. This work proposed a normalization method to solve this issue and to make it possible to implement in foundry fabrications. Since image-processing techniques have been matured in recent years, WBMs can be converted into binary images in the first stage. The conversion criteria is that every die will be converted into one binary pixel which good die is white and bad die is black, then one derived binary image will be obtained. In order to normalize the image, the image will be shrunk or expanded into 70x70 image size. The main pattern will still exist after stretching. Normalization can solve product-dependent issue in the learning stage. Figure 4 shows an example to translate WBM into binary image. In order to filter out the random noises, morphological operation was adopted. Figure 5 shows the example of morphological operation.

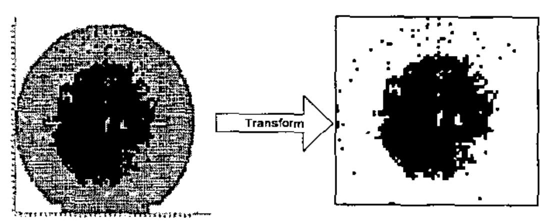


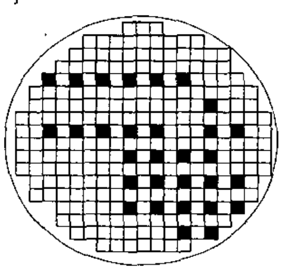
Figure 4 Transforming wafer bin map into binary image

Figure 5 Morphological operations on binary images

Features extraction

Features extraction could determine the performance of a learning neural network. It is therefore very important to select the features carefully. This work selected 4900 binary values of derived WBMs binary images as inputs of the neural network. But this feature is suitable for most failure patterns, except the repeating failure. Therefore, we chose two other features for repeating failure. The first one is row and column sum as shown in figure 6. The second is the reticle row size, reticle column size.

X_{ij}: *i*th row, *j*th column element of map
R_i: sum of *i*th row
C_j: sum of *j*th column



$$X_{ij} = \begin{cases} 1, \text{if die is failed.} \\ 0, \text{if die is passed.} \end{cases}$$

$$R_i = \sum_j X_{ij}$$

$$C_j = \sum_i X_{ij}$$

Figure 6 Row sum and column sum of WBMs

Models training

After the preprocess step of data normalization and features extraction, a supervised neural network was selected as the learning model. For center failure, edge failure and local failure, the 4900 binary values of binary image were selected as inputs of the learning model. And the output was a 4x1 vector. Figure 7 shows the proposed feed-forward neural network learning model for center failure, edge failure and local failure. It is a three-layer tan-sigmoid/ tan-sigmoid/log-sigmoid network and needs 4900 inputs and 4 neurons in its output layer to recognize the patterns. The log-sigmoid transfer function was adopted because its output range is ideal for learning to output Boolean values. Repeating failures are almost derived from lithography process and probe testing equipment and it cannot be recognized by image input directly, so we chose other two features for learning. Figure 8 shows the feed-forward neural network learning model to detect repeating failures. It needs 100 inputs and 2 neurons in its output layer to recognize if there exist repeating failures or not.

Verification

The last step is to verify the performance of the supervised neural network. There are two basic indexes, i.e., recognition hit rate and recognition speed. 260 test samples (7 products) were used to test the hit rate of learned neural network. The overall performance will be discussed in the next section.

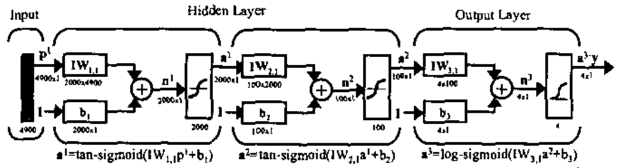


Figure 7 Neural network model I (modeled by MATLAB[10])

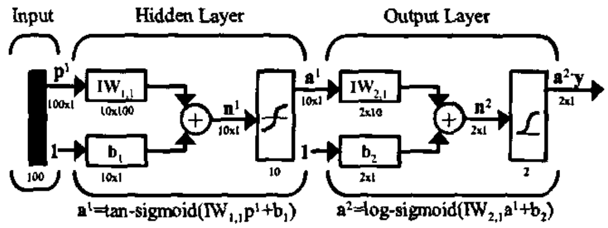


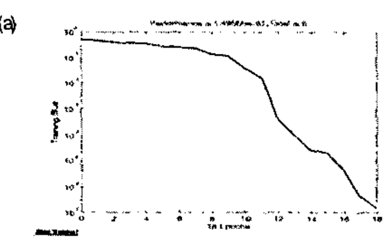
Figure 8 Model for repeating failure (modeled by MATLAB[10])

EXPERIMENTS AND RESULTS

Figure 9(a) shows the slope learning curve for repeating failures and figure 9(b) is the outputs of the neural network. Repeating failures can be recognized from the outputs easily. Figure 10 shows that the random-distributed map is recognized as repeating failure and metal one photo process is the root cause after verification. Table 1 shows the experiments results. Very low hit rate for repeating failure of network I because repeating failure pattern might be filtered out in morphological operation stage. After adding two other features of repeating failures, the hit rate can raise up to 98%. Features selection is very important and wrong features might lead to very poor results. This prototype shows that the extracted features can solve product-dependent issues and keep high hit rate.

Repeating failure:
(a) Learning curve for 25 positive/25 negative learning samples.
(b) Outputs for 5 positive/5 negative testing samples.

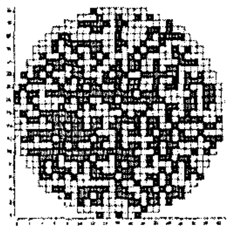
(a)



(b)

Sample	1	2	3	4	5
Positive	0.9996,0.0003	0.9996,0.0003	0.9996,0.0003	0.9996,0.0003	0.9995,0.0004
Negative	0, 0.9994	0, 0.9995	0, 0.9995	0, 0.9995	0, 0.9995

Figure 9 Sample results for repeating failure model



	1	2	3
1	58.95%	0.00%	52.08%
2	51.55%	48.42%	47.37%
3	60.00%	55.79%	53.26%

(a) Fails seem distributed randomly w/o reticle.
(b) It shows zero yield in position (1,2) of recticle.

Figure 10 Repeating failure example

Table 1. Experiment results

Model	Pattern Type	*# of* Train Sample	*# of* Test Sample	Correct	Hit Rate
Neural Network I	Center	25	61	60	98.36%
	Edge	25	29	27	93.10%
	Local	25	56	53	94.64%
	Repeat	25	24	1	4.17%
Neural Network II	Repeat	50	50	49	98.00%

CONCLUSIONS

Wafer Bin Maps (**WBMs**) are important for yield improvement to trace root causes. The characteristics of **WBMs** patterns are formed by processes, so process engineers can collect clues from the patterns and correlate them with specific processes. Tremendous amount of time and efforts in finding the root causes can therefore be saved. This work adopted a supervised learning methodology to develop an on-line **WBMs** pattern recognition system, which maps WBMs into 70x70 binary images to solve product dependent and too many derived patterns issues of unsupervised learning. A supervised **WBMs** pattern recognition framework is presented to improve the limitations. It can also detect repeating failures that are usually viewed as random patterns in the existing approaches. After evaluation and verification, this prototype shows good performance to detect center failure, edge failure, local failure and repeating failure. This prototype was developed by Math Works MATLAB R13 of Linux platform. In the future, it can be migrated to c++ codes, run on Windows platform, and integrated with the existing EDA system to aid engineers for yield enhancement. It can bring even more benefits if it is possible to integrate pattern recognition engine with MES system, especially for repeating failures that might cause customer's complaints due to reliability issue. Mixed pattern types are not discussed in this paper, but do exist in industry and need to be considered in the future work.

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