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MANUFACTURING INTELLIGENCE FOR DETERMINING MACHINE SUBGROUPS TO ENHANCE YIELD IN SEMICONDUCTOR MANUFACTURNING

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ABSTRACT

Linewidth control is a critical issue for yield enhancement in semiconductor manufacturing. Most of the existing techniques such as run-to-run control have been developed to control the critical dimension (CD) in photolithography and etching process. However, few studies have addressed the tool behavior that would also affect the result of CD in etching process and the etch bias that is the CD difference between photolithograph and etching process. This study aims to propose a manufacturing intelligence (MI) approach to develop dispatching rules for etching tool in order to reduce the variation of critical dimension measured after etching process and determine the machine subgroups for compensating the etching bias. An empirical study was conducted to estimate the validity of proposed approach and the results showed practical viability of this approach.

1 INTRODUCTION

With the shrinking feature size of integrated circuits (ICs) in advanced technology, the tolerance of critical dimension (CD) becomes tight and slight. Photolithography and etching are two main process for determining CD in semiconductor manufacturing. The CD is the minimum width of patterned line or the distance between two pattern lines. In particular, the measurement of CD after exposure and development in photolithography process is developed critical dimension (DCD) and the CD measured after etching process called etched critical dimension (ECD), which represents the final linewidth for each layer. The ECD directly affects semiconductor device performance. In order to assure product quality and process yield, ECD must be controlled within the tolerance precisely.

ECD variation may occur within a wafer, from wafer-to-wafer (W2W), from lot-to-lot (L2L) and between lots etched in different chambers. The CD variation occurred within a wafer is usually represented by the uniformity. It is generally a consequence of reactor design and determined by factors such as gas flow pattern, chamber symmetry and plasma source configuration. Wafer-to-wafer and lot-to-lot CD variation may occur because of poor repeatability at equipment, process and photolithography on incoming wafers (Petronis and Patrick 2003). The variation in different chambers is caused from the behavior of different etching equipments, which means the bias is in the chamber. However, most of the existing studies for advanced process control (APC) have investigated the CD variation reduction regarding the within-wafer, W2W and L2L CD control (El Chemali et al. 2003; Williams et al. 2005; Zhang, Poolla, and Spanos 2008; Parkinson et al. 2010). Little research addresses the CD control between lots etched in different chambers to compensate the bias in etching process.

This study aims to propose a manufacturing intelligence (MI) approach for estimating the effect of chamber and product and constructing a similarity measurement to reduce ECD variation between chambers. Indeed, MI approaches have been developed to extract useful information and derive decision rules from the data collected in the fully automated production facility to enhance yield and production effectiveness (Chien, Chen, and Peng 2010; Kuo, Chien, and Chen 2011). An empirical study was conducted in a fab in Taiwan to estimate the validity of proposed approach, and the process capability index, C_{pk}, was employed to present the performance. The derived similarity relationship between the etching equipments are used for dispatching of etching equipments and the fab has implemented the proposed approach for on line decision support.

2 FUNDAMENTAL

2.1 Critical Dimension (CD)

Both photolithography and etching processes influence the CD in semiconductor processes. The main purpose of photolithography process is to coat a layer of photoresist (PR) and transfer the mask pattern on the photoresist through exposure and development. The detail process steps in photolithography contains (1) dehydration back, (2) priming, (3) spin coating, (4) soft bake, (5) exposure, (6) post exposure bake, (7) development, and (8) hard bake. The DCD measurement is defined as the width of the positive photoresist as shown in Figure 1(a). In practice, it is usual to sample several wafers in a lot and measure several DCD values from different sites to calculate DCD mean in order to obtain the process performance. Existing control methods for DCD variation reduction focus on R2R approach (Lachman-Shalem, Grosman, and Lewin 2002; Grosman et al. 2005; Wu et al. 2008).

The etch process is to etch the thin film which is not coated by positive photoresist in order to form the mask pattern on the surface of wafer. After etching and removing the residual photoresist, ECD can be measured as shown in Figure 1(b). The difference between ECD and DCD comes from the effect of PR profile and etching technology. Like photolithography process, it is usually to measure several ECD values from different sites and calculate ECD mean as the representation for each lot in etch process.

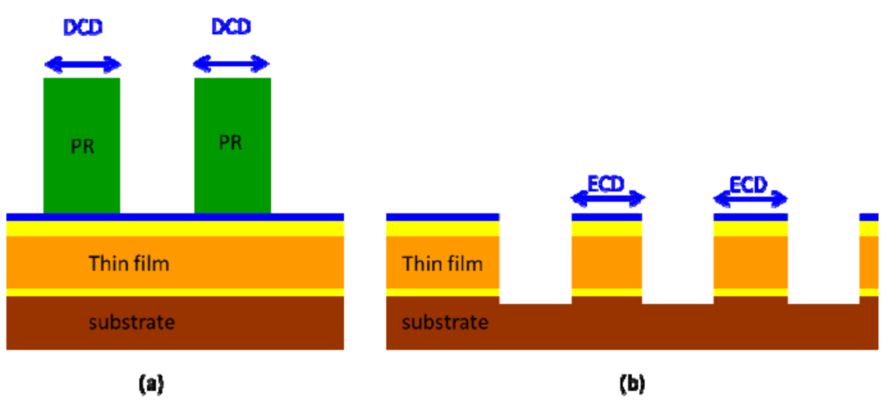

Figure 1: (a) DCD measurement in photolithography (b) ECD measurement in etch

2.2 Advanced Equipment Control/Advanced Process Control (AEC/APC)

AEC/APC was one of the objectives of the Microelectronics Manufacturing Science and Technology program begun in 1993, jointly funded by the Advanced Research Projects Agency, the US Air Force, and Texas Instruments (Fiorletta 2004). The goal of APC is to deliver process results that are consistently close to the target values. To deliver these results while tolerating incoming variation, it will be necessary to employ feedforword and feedback closed-loop control scheme. In terms of AEC, tool-level data can establish chamber baseline for tool and chamber matching, post-maintenance recovery, and process monitoring (Skumanich et al. 2004). SEMI (2009) defines a “complete” APC solution as a solution that provides an equipment data collection and management infrastructure, supports integration with other fab components such as the manufacturing execution system using appropriate integration standards, and provides the suite of APC applications including R2R control and fault detection and classification (FDC) techniques. In recent years, the APC evolution has matured with the focus shifting to integration of APC fab-wide, targeting broader objectives such as overall fab yields, throughput rates, and electrical characteristics in addition to the traditional process-centric goals (Bode and Sonderman 2004). Chien and Hsu (2006) clustered the machine into subgroups with similar characteristics and proposed an algorithm to prioritize the appropriate backups for specific machine based on the similarity measurement of overlay error.

3 PROPOSED APPROACH

The notations and coefficients generally used in this study are listed as follows:

E_i	etch bias defined as the difference between ECD and DCD for lot *i*;
μ	the population mean of etch bias;
$\hat{\mu}$	the estimated population mean (sample average) of etch bias;
β_p^{Prod}	the true effect for product *p*;
$\hat{\beta}_p^{\text{Prod}}$	the estimated effect for product *p*;
β_c^{chamber}	the true effect for etch chamber *c*;
$\hat{\beta}_c^{\text{chamber}}$	the estimated effect for etch chamber *c*;
$\left\{x_{ip}^{\text{Prod}}\right\}_{p=1}^{P}$	the set of indicator variable representing product types for lot *i*;
$\left\{x_{ic}^{\text{chamber}}\right\}_{c=1}^{C}$	the set of indicator variable representing etch chambers for lot *i*;
ε_i	random noise for lot *i*;
P	the total number of products;
C	the total number of chambers;
M	the total number of etch tools;
n	the total number of lots;
d_i^c	the similarity measurement of chamber *c* for lot *i*;
$T_i^{chanber}$	the chamber effect target for lot *i*;
$ECDT$	the ECD target;

The proposed approach consists of two steps. The first step is to estimate the effect of different products and chambers. Linear regression model is used to estimate the relationship between etch bias and its influence factors, i.e., product type and etch chamber, by using least squared method based on the historical data. The second step is to define the similarity measurement for etching chambers and tools, respectively. Through comparing the similarity of etch tool, the priority can be determined for each process lot coming from photolithography process.

3.1 Estimation of Chamber and Product Effects

ECD represents the final linewidth for each layer, and its variation is not only influenced by the variability occurring in etch process but also the output of photolithography process, i.e., DCD. If DCD deviates its target, it is easy to cause ECD to go off-target. On the other hand, the variability occurring in etch process must be controlled to maintain the stability of ECD. The etch bias defined as the difference between ECD and DCD is commonly used to present the variability in etch process. Therefore, the goal of reducing ECD variation is equivalent to reducing the etch bias variation. Focusing on the impact of etch chambers and product type for etch bias, this study constructs a linear regression model for modeling etch bias as follows:

$$E_i = \mu + \sum_{p=1}^{P} \beta_p^{\text{Prod}} x_{ip}^{\text{Prod}} + \sum_{c=1}^{C} \beta_j^{\text{chamber}} x_{ic}^{\text{chamber}} + \varepsilon_i, i = 1,\dots,n. \tag{1}$$

In order to estimate unknown parameters in (1), least squared method is used. After collecting the historical data, the linear regression model can be represented as the matrix form as follows:

$$\mathbf{Y} = \mathbf{Z\beta} + \boldsymbol{\varepsilon} \tag{2}$$

where

$$\mathbf{Y} = \begin{bmatrix} E_1 \\ \vdots \\ E_n \end{bmatrix};\ \mathbf{Z} = \begin{bmatrix} 1 & x_{11}^{\text{Prod}} & \cdots & x_{1p}^{\text{Prod}} & x_{11}^{\text{chamber}} & \cdots & x_{1c}^{\text{chamber}} \\ 1 & x_{21}^{\text{Prod}} & \cdots & x_{2p}^{\text{Prod}} & x_{21}^{\text{chamber}} & \cdots & x_{2c}^{\text{chamber}} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_{n1}^{\text{Prod}} & \cdots & x_{np}^{\text{Prod}} & x_{n1}^{\text{chamber}} & \cdots & x_{nc}^{\text{chamber}} \end{bmatrix};\mathbf{\beta} = \begin{bmatrix} \mu \\ \beta_1^{\text{Prod}} \\ \vdots \\ \beta_P^{\text{Prod}} \\ \beta_1^{\text{chamber}} \\ \vdots \\ \beta_C^{\text{chamber}} \end{bmatrix};\ \boldsymbol{\varepsilon} = \begin{bmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_n \end{bmatrix}.$$

Therefore, the least squared estimation of $\mathbf{\beta}$ can be calculated by (3) and the coefficient of determination, R^2, is used to evaluate the model fitness. If R^2 close to 1, it represents the variation of etch bias can be almost interpreted by product type and etch chambers.

$$\hat{\mathbf{\beta}} = (\mathbf{Z'Z})^{-1}\mathbf{Z'Y} \tag{3}$$

3.2 Similarity Measurement

Based on the result of parameter estimation, this study can define the similarity measurement for the etch chamber and tool, respectively. First, the etch chamber effect target for each lot coming from photolithography process is determined by using (4). The meaning of $T_i^{chamber}$ is that the chamber effect c which can meet this target is the best process chamber for lot i.

$$T_i^{chamber} = ECDT - DCD_i - \hat{\mu} - \text{Product effect}_i,\ i = 1,\dots,n. \tag{4}$$

Second, the similarity for each etch chamber is defined as (5) which is a distance deviation measurement. The deviation measurement not only considers the mean distance between estimated chamber effect and chamber effect target but also the variance of estimated chamber effect denoted as $\text{var}(\hat{\beta}_i^{\text{chamber}})$. The value of $\text{var}(\hat{\beta}_i^{\text{chamber}})$ can be obtained from the diagonal element of $(\mathbf{Z'Z})^{-1}$.

$$d_i^c = \frac{\left(\hat{\beta}_c^{\text{chamber}} - T_i^{chamber}\right)^2}{\text{var}(\hat{\beta}_c^{\text{chamber}})}, i = 1,...n; c = 1,..., C. \quad (5)$$

In practice, it is difficult to select a specific etch chamber for a lot due to the multi-chambers in an etching equipment. Calculation of the similarity for each etch tool is necessary to determine which tool is the best suited for the considered lot. However, different chambers in the same equipment may have different behavior of etching bias. This study applies the mini-max regret strategy (Savage 1972) to transform the chamber similarity into tool similarity. The min-max regret criterion is a conservative strategy which means that considering the worst case for each tool to select the better one. The largest d_i among all chambers is selected to represent the similarity of tool. Therefore, the dispatching priority of etch tool for each processing lot can be prioritized.

3.3 Result Evaluation

Process capability ratio (PCR) is used as a measure of the ability of the process to manufacture product that meets the specifications (Montgomery 2009). Thus, this study employs off-center process capability ratio, C_{pk}, as the performance index of etch process. The definition of C_{pk} is expressed as follow

$$C_{pk} = \min\left\{\frac{USL - \overline{X}}{3s}, \frac{\overline{X} - LSL}{3s}\right\} \quad (6)$$

where USL stands for upper specification limit, LSL stands for lower specification limit, $\overline{X}$ is the overall mean of ECD and s is the overall standard deviation of ECD. In this study, the performance index C_{pk} is calculated for each product on a specific layer.

4 EMPIRICAL STUDY

To validate the proposed approach in this study, an empirical study is conducted based on real production data collected from a semiconductor company in Taiwan. This company is an integrated semiconductor device manufacturer (IDM) that is a world leading provider for Mask ROM and Flash memory for various applications in consumer electronics. R2R techniques have been applied to control photolithography process in the wafer fab. Table 1 shows the comparison of present performance for 1-year historical data between DCD and ECD in terms of average and standard deviation. It is clear that ECD has higher variation than DCD, and the deviation between ECD overall mean and ECD target is also greater than DCD.

Table 1: Average and standard deviation of DCD and ECD

	DCD			ECD		
Product	N	Average	Standard Deviation	N	Average	Standard Deviation
A	481	0.2298	0.0034	337	0.2420	0.0049
B	295	0.2301	0.0030	214	0.2468	0.0044
C	379	0.2304	0.0025	250	0.2371	0.0041
D	275	0.2299	0.0026	232	0.2456	0.0045
E	126	0.2302	0.0032	77	0.2380	0.0046
Overall	1556	0.2301	0.0030	1110	0.2423	0.0058

DCD target: 0.23 ECD target: 0.24

4.1 Estimation of Chamber and Product Effects

The production data in two month are selected to construct the linear regression model. A total of 185 complete data points across 5 product types, 9 etch tools (18 chambers) are collected in the empirical study. ANOVA (analysis of variance) is used to evaluate the significance of product, chamber and metrology tool (i.e., scanning electron microscope, SEM) to etch bias. As shown in Table 2, product type and chamber are two significant factors for the variation of etch bias. Furthermore, the constructed linear model is expressed as follows:

$$E_i = \mu + \sum_{p=1}^{5} \beta_p^{\text{Prod}} x_{ip}^{\text{Prod}} + \sum_{c=1}^{18} \beta_j^{\text{chamber}} x_{ic}^{\text{chamber}} + \varepsilon_i, \quad i = 1,\ldots,185.$$

Table 2: ANOVA table for etch bias

Source	SS	df	MS	F	p-value
Product	0.012	4	0.003	267.861	0.000
Chamber	0.006	17	0.000	30.043	0.000
SEM	0.000	4	0.000	1.383	0.238
Error	0.010	915	0.000		
Total	0.027	940			

The estimated parameters in this model are listed in Table 3. The R-square of proposed model is around 0.65. There are two products with negative effect on etch bias, and the rest three products have positive effect on etch bias. Similarly, we can roughly divide 18 chambers into two groups: one with negative effect on etch bias, and the other one with positive impact.

Table 3: Results of parameter estimation

Parameter	μ	β_1^{Prod}	β_2^{Prod}	β_3^{Prod}	β_4^{Prod}	β_5^{Prod}	β_1^{chamber}	β_2^{chamber}
Estimation	0.0138	0.002	0.0046	-0.0057	0.0036	-0.0045	-0.0029	0.0002
Variance							0.1224	0.1374
Parameter	β_3^{chamber}	β_4^{chamber}	β_5^{chamber}	β_6^{chamber}	β_7^{chamber}	β_8^{chamber}	β_9^{chamber}	$\beta_{10}^{\text{chamber}}$
Estimation	0.0003	-0.0029	0.002	0.0015	-0.0007	0.0008	-0.0062	-0.0012
Variance	0.1409	0.1914	0.3091	0.0717	0.0536	0.1251	0.0716	0.096
Parameter	$\beta_{11}^{\text{chamber}}$	$\beta_{12}^{\text{chamber}}$	$\beta_{13}^{\text{chamber}}$	$\beta_{14}^{\text{chamber}}$	$\beta_{15}^{\text{chamber}}$	$\beta_{16}^{\text{chamber}}$	$\beta_{17}^{\text{chamber}}$	$\beta_{18}^{\text{chamber}}$
Estimation	0.0018	0.003	-0.0011	0.0052	0.0031	0.004	0.0008	-0.0075
Variance	0.0915	0.0937	0.1009	0.0669	0.2385	0.0926	0.0921	0.1226

4.2 Similarity Measurement

Based on the result of parameter estimation, the chamber similarity can be calculated. A lot which has 0.221 for DCD is used for illustration of the determining tool similarity. Give the DCD and ECD target is 0.23 and 0.24, respectively, the chamber effect target can be calculated based on equation (4) as follows.

$$T_i^{chamber} = 0.24 - 0.221 - 0.0138 - 0.0046 = 0.0006$$

The chamber similarity and tool similarity for this lot is shown in Table 4. Tool 3 is the first priority for the selected lot, and it contains chamber No. 5 and 6. The second priority and third priority are tool No. 4 and 6, and they consist of chamber 7/8 and 11/12, respectively. Observing the effect of these 6 chambers, we can find that most of them are positive. This result satisfies the intuition since the measured

DCD is lower than DCD target. According to calculated tool priority, this lot is assigned to Tool 3 to execute the process first. If Tool 3 cannot be operated for this lot, then it will be assigned to Tool 4.

Table 4: An numerical example for similarity measurement

Tool No.	*Chamber No.*	*Chamber similarity*	*Tool similarity*	*Tool priority*
1	1 2	0.000100 0.000001	0.000100	5
2	3 4	0.000001 0.000064	0.000064	4
3	**5** **6**	**0.000006** **0.000011**	**0.000011**	**1**
4	**7** **8**	**0.000032** **0.000000**	**0.000032**	**2**
5	9 10	0.000646 0.000034	0.000646	9
6	**11** **12**	**0.000016** **0.000061**	**0.000061**	**3**
7	13 14	0.000029 0.000316	0.000316	7
8	15 16	0.000026 0.000125	0.000125	6
9	17 18	0.000000 0.000535	0.000535	8

4.3 Result Evaluation

Since the determination of tool similarity affects the tool priority and thus influence the performance, this study creates a scenario analysis to compare two different strategies, proposed mini-max regret strategy and expectation strategy. In this study, the expectation strategy for tool similarity is the average of chamber similarities plus a penalty for deviation of chamber similarities. The expectation strategy assumes every chamber in a tool has an equal chance to process a specific lot and gives higher priority for the tool which contains more similar chambers. Unlike expectation strategy, mini-max regret strategy uses the worst chamber similarity as the tool similarity directly instead of assuming entry probability. This study collects another one month historical data and applies above estimated parameters to calculate chamber similarity for each lot. This study considers five scenarios with different entry probabilities of chambers and calculates corresponding results by assuming each lot will enter the first priority tool. Table 5 and Table 6 summarize the results of scenario analysis for expectation strategy and mini-max regret strategy, respectively. By comparing Table 5 and Table 6, we can find that expectation strategy has higher overall C_{pk} while mini-max regret strategy can reduce the C_{pk} difference between products. While the scenario analysis for expectation strategy shows two negative C_{pk} improvement values, mini-max regret strategy shows all positive improvement. It means that the proposed mini-max regret strategy is more robust comparing to expectation strategy.

The proposed approach now is implemented in the wafer fab. Table 7 shows the summarized performance of applying the proposed approach. Indeed, the proposed approach can enhance C_{pk} for most products. Although the proposed approach can provide appropriate tool priority when a lot goes to etch process, the actual performance could be affected by the management situation and other constraints in the wafer fab.

Table 5: Scenario analysis for expectation strategy

	Product	A	B	C	D	E	overall	C_{pk} deviation within products
Present Performance	C_{pk}	1.60	0.97	1.97	1.01	2.10	1.05	
	N	26	25	22	16	27	116	0.5262
Scenario 1: (0.54, 0.46)	C_{pk}	1.61	1.42	2.48	1.86	3.38	1.72	0.7954
	improve	0.54%	46.16%	25.76%	84.19%	60.91%	64.39%	
Scenario 2: (0.7, 0.3)	C_{pk}	1.53	1.47	2.51	1.78	3.47	1.76	0.8449
	improve	-4.17%	52.33%	27.63%	76.02%	65.30%	68.47%	
Scenario 3: (0.3, 0.7)	C_{pk}	1.69	1.44	2.42	1.97	3.17	1.64	0.6820
	improve	5.81%	48.34%	23.17%	95.47%	51.01%	56.38%	
Scenario 4: (0.9, 0.1)	C_{pk}	1.51	1.58	2.54	1.90	3.63	1.88	0.8812
	improve	-5.65%	62.91%	28.95%	88.82%	72.97%	79.63%	
Scenario 5: (0.1, 0.9)	C_{pk}	1.82	1.58	2.38	2.26	3.05	1.61	0.5669
	improve	13.88%	62.78%	21.04%	123.96%	45.39%	53.28%	

Table 6: Scenario analysis for mini-max regret strategy

	Product	A	B	C	D	E	overall	C_{pk} deviation within products
Present Performance	C_{pk}	1.60	0.97	1.97	1.01	2.10	1.05	
	N	26	25	22	16	27	116	0.5262
Scenario 1: (0.54, 0.46)	C_{pk}	1.69	1.32	2.49	1.90	3.15	1.61	0.7195
	improve	5.80%	35.84%	26.34%	88.55%	49.94%	53.67%	
Scenario 2: (0.7, 0.3)	C_{pk}	1.78	1.24	2.50	1.88	3.16	1.60	0.7371
	improve	11.25%	27.63%	27.03%	85.86%	50.49%	53.10%	
Scenario 3: (0.3, 0.7)	C_{pk}	1.69	1.49	2.44	2.00	3.20	1.64	0.6811
	improve	5.79%	54.23%	23.76%	98.21%	52.23%	56.19%	
Scenario 4: (0.9, 0.1)	C_{pk}	1.97	1.15	2.56	1.87	3.13	1.61	0.7481
	improve	22.93%	19.09%	29.79%	84.94%	49.07%	54.14%	
Scenario 5: (0.1, 0.9)	C_{pk}	1.81	1.65	2.38	2.21	3.22	1.66	0.6150
	improve	13.07%	70.17%	20.85%	118.93%	53.47%	58.52%	

Table 7: Summarized results for online implementation of proposed approach

Product	Before implementation		After implementation		C_{pk} improvement
	N	C_{pk}	N	C_{pk}	
A	60	1.58	29	1.76	11.39%
B	42	1.33	17	1.26	-5.3%
C	27	1.67	16	1.81	8.4%
F	35	1.30	25	2.44	87.69%
G	56	1.18	62	1.48	25.42%

5 CONCLUSION

This study develops a MI approach for determining machine groups based on the similarity estimated from different products and chambers to thus reduce the yield loss due to the mismatch. The influence factors of etch bias were investigated. Modeling etch bias provides the estimation of product effects and chamber effects, and these parameters can be used to determine the similarity of etch chamber (tool). We validated the proposed approach with an empirical study from a wafer fab. The result demonstrated that the derived dispatching rule can enhance ECD C_{pk} at least 25%. Considering the tradeoffs between operation efficiency and yield loss, the proposed approach can effectively determine the priority of dispatching machine.

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