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An Effective SPC Approach to Monitoring Semiconductor Manufacturing Processes with Multiple Variation Sources

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Abstract – In this research, we develop an integrated sampling and statistical process control (SPC) strategy for semiconductor processes with multiple variation sources. We first construct a process model to characterize the complex nature of semiconductor processes. Three types of variations: among-site, among-zone and among-batch variations, are considered in the model. Based on this process model and rational sub-grouping techniques, multivariate T^2 control charts are then proposed to monitor the process variations. It is shown that the proposed control charts are more effective than conventional charting techniques in detecting various types of process excursions.

Index Terms – Rational sub-grouping, Statistical process control (SPC), Multivariate T^2 control chart

INTRODUCTION

The problem most often encountered by process engineers when doing SPC charting [1] in semiconductor fabrication is the difficulty to arrange and group the sample data and to properly construct and interpret the control charts. Due to the high cost of test wafers and metrology, only few sample wafers are taken from a lot or a process run. Sample readings are then taken from the sample wafers. For example, after oxidation process (Fig. 1) five thickness readings will be taken from each of three sample wafers (Fig. 2), which in turn are taken from three different zones (top, center, and bottom) of the oxidation furnace in a process batch.

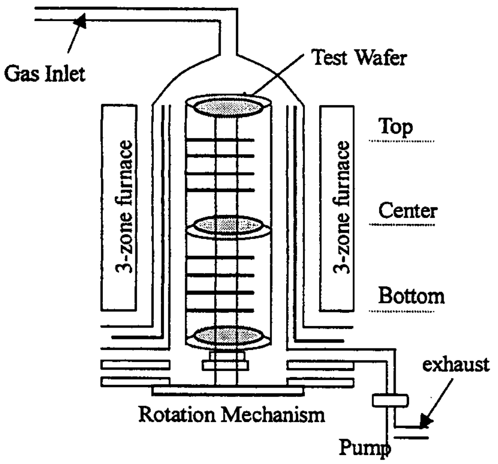


Fig. 1 Oxidation furance

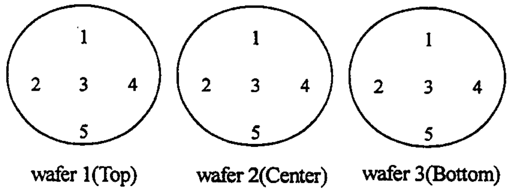


Fig. 2 Rational sampling of oxidation thickness

There are various variation components in this process: batch-to-batch, wafer-to-wafer, and site-to-site variations, and interactions among variation sources. Each variation component has its own implication for different processing problems [2]. With the sample thickness readings shown in Fig. 2, how should engineers group the data and construct control charts to monitor these variation components? In this research, we first present an analysis of variance (ANOVA) that decomposes and discerns significant variation sources. Such analyses provide insights on what sources of variation should be watched more closely. Table 1 shows an ANOVA for the oxidation thickness.

Table 1: ANOVA for Oxidation Thickness

ANOVA

Source	DF	SS	MS	F	Pr>F
Batch(*b*)	44	1397.82	31.77	7.33	0.0001
Wafer(*w*)	2	983.43	491.72	113.43	0.0001
Position(*p*)	4	1298.23	324.56	74.87	0.0001
wxp	8	669.57	83.70	19.31	0.0001
Error	616	2670.36	4.34		
Total	674	7019.42			

From the analysis of variance, significant variation sources can be found. Control charts are therefore constructed to monitor these variation sources. Fig.2 shows the four batch-to-batch control chart that are most often seen in practice. One is an "overall" batch-to-batch chart in that each data point is the average of all 15 readings from one processing batch. The other three $\overline{X}-R$ charts are "zone" batch-to-batch charts. Wafers 1, 2, 3 are taken, respectively, from top, center, and bottom zones of a vertical oxidation furnace. Each data point on a "zone" batch-to-batch chart represents the average or range of the 5 readings from one wafer. From Fig. 3, the process seems running OK since all data points are within the control limits.

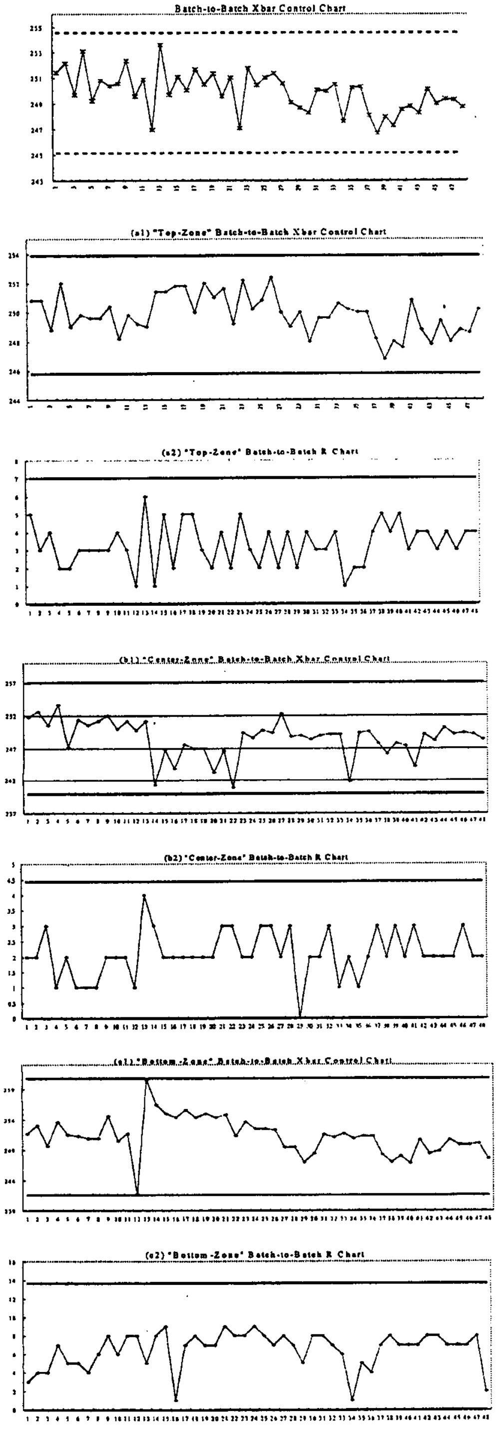


Fig. 3 Four most used batch-to-batch control charts

To capture all variation sources, it is, however, not sufficient to only rearrange and regroup the sample data. The conventional way of constructing control charts will result in too many control charts with too many false alarms. In this research, we first build a process model to characterize the complex nature of the semicondutor processes [3-4]. Based on the process model, we then propose an integrated, effective SPC approach, i.e. four multivariate T^2 control charts [5-6], that can detect excursions from all types of variation sources.

STATISTICAL PROCESS MODEL

We start with constructing a model that can describe all possible situations such as correlation and fixed differences among quality measurements. As mentioned earlier, the model should be capable of characterizing the complex relationship among the variation sources. In this paper, we propose a model as shown in Eq. (1), which is capable of characterizing the most complicated situations and certainly explains a large class of semiconductor manufacturing processes.

$$X_{ijk} = \mu + b_i + w_{j(i)} + p_{jk(i)} \quad j=1..m\text{，}k=1..n \quad (1)$$

where b_i、$p_{jk(i)}$、$w_{j(i)}$ are independent of one another;
$b_i \sim N(0,\sigma_b^2)$;
$w_{(i)}=[w_{j(i)}]_{m\times 1} \sim N(\mu_w\text{，}\Sigma_w)$;
μ_w is an $m\times 1$ mean vector;
Σ_w is an $m\times m$covariance matrix;
$p_{j(i)}=[p_{jk(i)}]_{m\times 1} \sim N(\mu_j\text{，}\Sigma_j)$;
μ_j is an $n\times 1$ mean vector; and
Σ_j is an $n\times n$ covariance matrix.

Based on Fig. 2, m=3 and$n$=5. That is,

$$w_{(i)} = \begin{bmatrix} w_{1(i)} \\ w_{2(i)} \\ w_{3(i)} \end{bmatrix} \sim N(\mu_w, \Sigma_w) = N\left(\begin{bmatrix} \mu_{w_1} \\ \mu_{w_2} \\ \mu_{w_3} \end{bmatrix}, \begin{bmatrix} \sigma_{w_1}^2 & \sigma_{w_1,w_2} & \sigma_{w_1,w_3} \\ \sigma_{w_1,w_2} & \sigma_{w_2}^2 & \sigma_{w_2,w_3} \\ \sigma_{w_1,w_3} & \sigma_{w_2,w_3} & \sigma_{w_3}^2 \end{bmatrix} \right)$$

$$p_{j(i)} = \begin{bmatrix} p_{j1(i)} \\ p_{j2(i)} \\ p_{j3(i)} \\ p_{j4(i)} \\ p_{j5(i)} \end{bmatrix} \sim N(\mu_j, \Sigma_j)$$

$$= N\left(\begin{bmatrix} \mu_{j1} \\ \mu_{j2} \\ \mu_{j3} \\ \mu_{j4} \\ \mu_{j5} \end{bmatrix}, \begin{bmatrix} \sigma_{j1}^2 & \sigma_{j1,j2} & \sigma_{j1,j3} & \sigma_{j1,j4} & \sigma_{j1,j5} \\ \sigma_{j1,j2} & \sigma_{j2}^2 & \sigma_{j2,j3} & \sigma_{j2,j4} & \sigma_{j2,j5} \\ \sigma_{j1,j3} & \sigma_{j2,j3} & \sigma_{j3}^2 & \sigma_{j3,j4} & \sigma_{j3,j5} \\ \sigma_{j1,j4} & \sigma_{j2,j4} & \sigma_{j3,j4} & \sigma_{j4}^2 & \sigma_{j4,j5} \\ \sigma_{j1,j5} & \sigma_{j2,j5} & \sigma_{j3,j5} & \sigma_{j4,j5} & \sigma_{j5}^2 \end{bmatrix} \right) \quad j=1..3$$

$$且 \sum_{j=1}^{m} \mu_{w_j} = 0 \quad , \quad \sum_{k=1}^{n} \mu_{jk} = 0 \ , \ j = 1..m \ 。$$

Fig. 4 shows the relationship of various variation components based on the rational smapling scheme in Fig. 2.

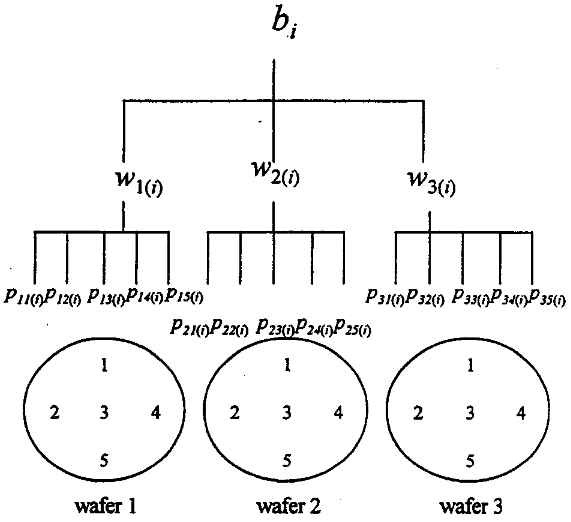


Fig. 4 Variation components of model (1)

A typical sampling plan will take ($j=$) m wafers from each batch (i) of wafers and ($k=$) n readings from each wafer. In the model above, b_i represents the effect of the ith batch of wafers and follows a normal distribution. $w_{(i)}$ denotes the wafer (zone) variation effect at batch i and is a ($m \times 1$) vector following a multivariate normal distribution. The element $w_{j(i)}$ denotes the effects of the jth wafer in the same batch. $p_{j(i)}$ denote the variation effect of positions on the jth wafer (zone) and is a ($n \times 1$) vector also following a multivariate normal distribution. Its element $p_{jk(i)}$ represents the effect of the kth position of the jth wafer. Only with these multivariate variables, be the model able to capture all kinds of effects and variation components.

CONTROL CHARTS CONSTRUCTION

Based on the prosposed model, there are three variation sources (b、w、p) that will affect the thickness observation X. Therefore, we will construct control charts to detect out-of control incidents caused by different variation sources. There will be four multivariate control charts:

1. position (site) effect chart for wafer 1 (top zone)
2. position effect chart for wafer 2 (center zone)
3. position effect chart for wafer 3 (bottom zone) and
4. wafer effect chart

and one batch-to-batch univariate control chart.

However, in model (1) there are too many parameters to be estimated for control chart construction. The observations X_{ijk} are not sufficient to estimate all the model parameters. In this research, we propose using observation differences to construct control charts

Control Charts for Position Difference

We define new variable $\nabla p_{jk(i)} = p_{jk(i)} - p_{jk+1(i)}$ to represent the thickness difference between postions k and k+1 on the jth wafer (zone) of batch i:

$$\nabla p_{jk(i)} = p_{jk(i)} - p_{j\,k+1(i)}$$
$$= X_{ijk} - X_{ij\,k+1} = \left(\mu + b_i + w_{j(i)} + p_{jk(i)}\right) - \left(\mu + b_i + w_{j(i)} + p_{j\,k+1(i)}\right.$$
$$j = 1..m \qquad k = 1...n-1$$

Let $\nabla \boldsymbol{p}_{j(i)}$ be the vector of thickness differences among positions on the jth wafer of batch i:

$$\nabla \boldsymbol{p}_{j(i)} = \begin{bmatrix} \nabla p_{j1(i)} \\ \nabla p_{j2(i)} \\ \vdots \\ \nabla p_{jn-2(i)} \\ \nabla p_{jn-1(i)} \end{bmatrix} \sim N\left(\mu_{\nabla p_j}, \Sigma_{\nabla p_j}\right) \quad j=1..m$$

We then construct a T^2 control chart for this vector. Its ith batch T^2 statistic is:

$$T^2_{\nabla p_{j(i)}} = \left(\nabla \boldsymbol{p}_{j(i)} - \hat{\mu}_{\nabla p_{j(i)}}\right)' S^{-1}_{\nabla p_j} \left(\nabla \boldsymbol{p}_{j(i)} - \hat{\mu}_{\nabla p_{j(i)}}\right)$$

where $\hat{\mu}_{\nabla p_j}$ $(=[\hat{\mu}_{\nabla p_j}]_{(n-1)\times 1})$ is the estimate of the mean vector $\mu_{\nabla p_j}$, $S_{\nabla p_j}$ is the estimate of the covariance matrix $\Sigma_{\nabla p_j}$. The control limits are:

$$(UCL_p)\ T^2_{n-1,r,1-\alpha/2} = \frac{r(n-1)}{(r-n+2)} * F_{n-1,r-n+2,1-\alpha/2}$$

$$(LCL_p)\ T^2_{n-1,r,\alpha/2} = \frac{r(n-1)}{(r-n+2)} * F_{n-1,r-n+2,\alpha/2}$$

By using our approach, all variation source

When the control chart signals an out-of-control incident, it indicates that a process excursion is caused by the varation source wafer j. Further investigation can be then more focused on the root causes that incurs the thickness deviations among postions on wafer j.

Control Charts for Wafer Difference

Similarly, we define new variable $\nabla \omega_{j(i)} = \sum_{k=1}^{n} X_{ijk} - \sum_{k=1}^{n} X_{ij+1k} = X_{ij\bullet} - X_{i\,j+1\bullet}$ to represent the thickness difference between wafers j and j+1 in batch i. Let $\nabla \omega_{(i)}$ be the vector of thickness differences among wafers in the ith batch:

$$\nabla \omega_{(i)} = [\nabla \omega_{j(i)}]_{(m-1)\times 1} = \begin{bmatrix} \nabla w_{1(i)} \\ \vdots \\ \nabla w_{m-1(i)} \end{bmatrix} \sim N(\mu_{\nabla w}, \Sigma_{\nabla w}).$$

We then construct a T^2 control chart for this vector. Its ith batch T^2 statistic is:

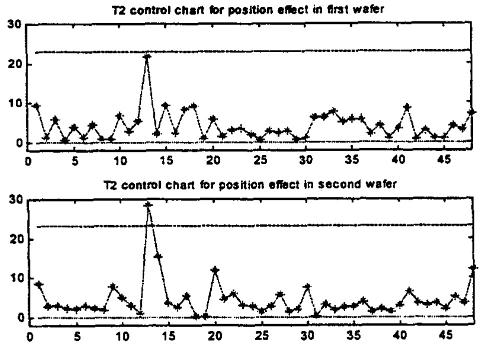
$$T^2_{\nabla\omega_{(i)}} = \left(\nabla\omega_{(i)} - \hat{\mu}_{\nabla\omega}\right)' \mathbf{S}_{\nabla\omega} \left(\nabla\omega_{(i)} - \hat{\mu}_{\nabla\omega}\right)$$

where $\hat{\mu}_{\nabla\omega}$ $(=[\hat{\mu}_{\nabla\omega_j}]_{(m-1)\times 1})$ is the estimate of the mean vector $\mu_{\nabla\omega}$; $S_{\nabla\omega}$ is the estimate of the covariance matrix$\Sigma_{\nabla\omega}$. We construct an MCUSUM chart:

$$MC_i^+ = \max\left(0, MC_{(i-1)}^+ + T_i - k_1\sigma_{T^2_{\nabla\omega}}\right) \quad MC_0^- \geq 0 \quad k_1 > 0$$
$$MC_i^- = \max\left(0, MC_{(i-1)}^- + k_2\sigma_{T^2_{\nabla\omega}} - T_i\right) \quad MC_0^- \geq 0 \quad k_2 > 0$$

where $\sigma_{T^2_{\nabla\omega}}$ is the standard deviation fo $T^2_{\nabla\omega}$.
When $MC_i^+ > h_1\sigma_{T^2_{\nabla\omega}}$ (=H1) or $MC_i^- > h_2\sigma_{T^2_{\nabla\omega}}$ (=H2),

Fig. 5 shows these four T^2 charts. It is seen that the control chart can effectively detect the problem batches 12, 13, and 29 and their corresponding variation sources. In conclusion, the proposed SPC approach is shown to be very effective in detecting process excursions with multiple variation sources and is also robust by keeping the in-control data points well within the control limits. This technique is especially useful for semiconductor manufacturing. Post-process sample data, such as thickness, CD and alignment data, can be effectively monitored. The technique can also provide engineers useful information on the source of excursion.



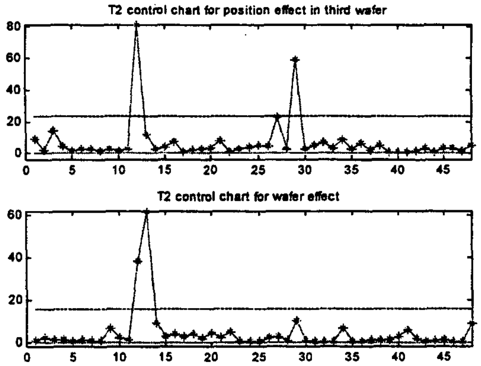


Fig. 5 T^2 control charts for multiple variation sources

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