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半導體產業中製程監控之取樣策略
Sampling Strategies for Process Monitoring in Semiconductor Industry

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中文摘要

線上檢測是半導體製程中非常重要之步驟。由於半導體製造過程相當昂貴，一片晶圓在經過每一步製程，其附加產值都將明顯增加。為了有效地偵測出製程偏移以減少生產損失並改善良率，極為關鍵的步驟便是使用線上檢測方法，一個有效率之取樣策略將有助於使線上檢測能真正達到改善良率的目的。然而，複雜的製造過程使線上取樣亦成為不易之工作。在本計畫中，我們將發展出一套整合取樣策略。我們尤其將重點放在提昇統計製程管制圖（statistical process control charts**）和扁移製程檢出之功能。為達此目的，我們必須考慮一些關鍵因素並找出一合理分組（**rational subgrouping**）與管制圖建構策略且降低最後生產總成本。一個有效率的管制圖建構策略應配合合理分組使其功能發揮至最大並縮短檢出扁移原因所需時間。除了合理分組外，我們亦需考慮如何去平衡檢測及生產損失成本。為了使檢測之規畫更為經濟而有效率，我們必須決定那些是需要檢測之關鍵製程步驟。本計畫之主要目的是去發展出一有效率之取樣及管制圖建構方法，這方法不但可使管制圖發揮其最大功能，亦可使檢測及生產總成本降至最低。**

關鍵詞：取樣策略，統計製程控制，良率改善，線上檢測

1. Abstract

In-line inspections are very important steps in semiconductor manufacturing processes. Due to the significant amount of value added on a wafer at each process step, the in-line inspection has become a crucial means to detect process excursions and to improve the manufacturing yield. An effective sampling strategy will help to achieve these goals. However, the complex nature of the manufacturing processes and the inspection technologies makes the data sampling an intricate task. In this project, we develop an integrated sampling strategy. Particularly, we focus on the strategy to achieve effective statistical process control (SPC) and process excursion investigation. To accomplish this, some key factors should be taken into considerations to determine a rational subgrouping strategy and to minimize the total cost. A rational subgroup is an inspection sample that is taken in-line and represents a homogeneous group within which sample measurements vary due only to a constant system of common causes. Choosing an effective rational subgrouping strategy and constructing corresponding control charts can maximize the power of the control chart and minimize the excursion investigation efforts. In addition to rational subgrouping and control chart construction strategies, we also need to consider the trade-off between the yield and the inspection cost. To make the inspection scheme more cost-effective, inspection points for critical process steps (layers) should be determined. The objective of this project is to develop an integrated sampling and chart construction approaches that maximize the power of SPC charts and minimizes the costs of inspections and yield loss in IC fabrication processes.

Keywords: sampling strategy, SPC, yield improvement, In-line inspection

2. Background and Objective

Wafer inspections are the crucial means to improve the production yield in the state-of-the-art semiconductor manufacturing processes. Since each process step adds significant amount of value on the wafers, tight process monitoring via in-line inspections is necessary for early detection of manufacturing problems. By discovering and eliminating causes of process excursions, the production yield can be then improved significantly. The monitoring tool widely used in the industry is the statistical process control (SPC) chart [Cunningham et al.(1995), Shanks (1996), and Leang et al. (1996)].

A control chart is a graphical record of sample data to track the process over time. It consists of upper and lower control limits that represent the decision boundary for a statistical hypothesis test. When a sample statistic falls outside the limits, a process excursion (out-of-control state) is said to occur. It is at this event, an investigation takes place to find the cause that led to the process excursion.

To employ an SPC chart, the chart must be constructed first and several variables should be determined. The variables include the sampling frequency, the sample size, and the decision boundary. There are two approaches to constructing a Shewhart control chart. The first is to determine a rational sampling strategy by carefully examining variation sources of the process [DeVor, et al. (1992) Chap. 7]. The second is to minimize the total loss based on a cost model [Duncan (1956), Lorenzen and Vance (1986), and Elsayed and Chen (1994)]. While the former focuses on maximizing the power of the control chart and does not compromise with the out-of-control processes, the latter intends to minimize the total cost by considering the trade-off between the inspection cost and yield loss. In practice, the rational sampling approach is broadly adopted but is too process-specific to be discussed in the more generic academic setting. The cost-based approach, on the other hand, receives many researchers' attention but is mostly ignored by the practitioners due to its mathematical complexity and unrealistic assumptions.

The complexity of both approaches is further magnified when applied in semiconductor processes. This is because the nature of IC fabrication is very complex by itself. Nurani et al. (1996) and McIntyre et al. (1996) are the first, and by far the only, to investigate the problem. They extend the cost-based approach by introducing additional factors and variables specific to the IC fabrication processes. Their approach, however, overlooks the issues of rational subgrouping. Without maximizing the control chart power, the model suffers from biased cost estimates of yield loss. The approach also inherits from the traditional cost-based model many unrealistic or ungrounded assumptions. Another problem of the approach is that the complicated mathematical model with numerous assumptions will make it slow to react to the fast-paced IC fabrication technologies.

In this project, we first develop integrated sampling and control chart construction approaches that maximize the SPC chart power by considering various variation sources [Roes and Does (1995), Woodall and Thomas (1995) and Boning and Chung (1996)]. In our research, multivariate control charts [Jackson (1986) and Montgomery (1995)] will be effectively constructed to monitor the nested variation sources.

In addition to the effective control chart monitoring, 100% inspection points are usually allocated among process steps to sort out defective in-process wafers and to prevent nonconforming wafers from being further processed and shipped to customers. The objective of the allocation problem is to determine the optimum inspection locations such that a specified outgoing quality level is met and/or the expected total cost is minimized.

Lindsay and Bishop (1964) are the first to propose an economic model to validate the rule for inspection of in-process items. They consider the situation where a penalty cost is associated with each defective finished item and the total final cost is to be minimized. They develop a dynamic programming approach to find the location of 100% inspection points among the production stages. Though Lindsay and Bishops' model has been intensively extended in the literature [Raz (1986)], it is still a comprehensive model that is relatively easy to apply in practice. Important modifications and extensions include White (1966), Pruzan and Jackson (1967), and Eppen and Hurst (1974). However, the drastic increase in the complexity often forces researchers to drop some features.

The second objective of this project is to demonstrate an alternative dynamic programming approach that uses the expected cost of discovering and discarding *one* defective item as an intermediate objective function during the process of solution search. It is proved that the approach eventually minimizes the expected total cost. The alternative approach will be illustrated using the same example given in Lindsay and Bishop (1964).

3. Results and Discussions

Our research results can be organized into two parts: the first, effective sampling and control charts construction, and the second, optimal allocation of critical inspection points. Each research result will be accompanied by some discussion.

3.1 Effective control chart construction for processes with various variation sources

We start with constructing a model that can describe all possible situations such as correlation and fixed differences among quality measurements. In our research we have constructed two models for two situations with different degrees of complexity. The only difference between these two models is that one model has the capability of describing the interaction between effects of the wafer and position on the quality measurements while the other model is simplified and lacks this capability. In this report, we shall show the model for the simpler situation but still capable of explaining a large class of practical situations.

$$X_{ijk} = \text{«} + b_1 + w_{j(i)} + p_{k(i)}$$

$i=1..r$, $j=1..m$, $k=1..n$

where $b_i \sim N(0,\sigma_b)$, $W=[w_j]_{m\times 1} \sim N(\mu_{m\times 1(w)}, \Sigma_{m\times m(w)})$, and $P=[p_k]_{n\times 1} \sim N(\mu_{n\times 1(p)}, \Sigma_{n\times n(p)})$

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 is a ($m \times 1$) vector and follows a multivariate normal distribution. The element w_j denotes the effects of the jth wafer in the same batch. P is a ($n \times 1$) vector and also follows the multivariate normal distribution. Its element p_k represents the effects of the kth position of the wafer. Only with these multivariate variables, be the model able to capture all kinds of effects and variation components.

We assume in our model that there exist fixed differences among wafers and among positions on the wafer. In addition, every observation of X is affected by 3 types of variation components: b, w, and p. To construct corresponding SPC charts, we should consider these fixed differences and variation sources. This will help diagnose the root causes of out-of-control process and enable the more effective corrective actions. Take the CVD (chemical vapor deposition) process as an example. The quality characteristic of concern is the film thickness grown in the process. There exist three types of variation components: variation among positions on a wafer, variation among wafers and variation among batches of wafers. Correspondingly, we construct three types of control charts. However, due to the number of variation components is quite large, it is difficult to estimate all the variances and covariance in the model. To overcome this difficulty, we take the difference of the observations and construct control charts for these differences instead. For example, X_{i22} denotes the thickness reading from the second position of wafer 2 in batch i. There are 4 components in X_{i22}: «, b_i, $w_{2(i)}$, and $p_{2(i)}$. Similarly, X_{i23} consists of four components: «, b_i, $w_{2(i)}$, and $p_{3(i)}$. By taking the difference of X_{i22} and X_{i23}, we are able to remove the effects of «, b_i, and $w_{2(i)}$ to obtain $p_{2(i)} - p_{3(i)}$, that is, the variation component only affected by the position difference. We can then follow to construct control charts for monitoring the variation component induced by position differences. Using the same method, we can also construct control charts for the variation component by wafer differences.

Let us first construct multivariate T^2 control charts for position differences:

$$dp_{k(i)} = X_{i\bullet k} - X_{i\bullet k+1} \qquad k = 1...n-1 \tag{2-1}$$

$dp_{k(i)}$ represents the difference between readings from position k and $k+1$. We can then construct n-1 T^2 charts for dp's:

$$T^2_{(i)} = (dp_{(i)} - \overline{dp})' \, S_{dp}^{-1} \, (dp_{(i)} - \overline{dp})$$

Where $dp_{(i)}$ is the ith observation. Since there are n readings from every wafer, the reading differences form a $(n-1)$ò1vector: [$dp_{1(i)}$ $dp_{2(i)}$ $dp_{3(i)}$ $dp_{4(i)}$]. Also, $\overline{dp}$ denotes the average of dp and S_{dp} is the estimated covariance matrix of dp. The control limit (CLp) becomes

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

When this control limit is exceeded, a possible fault is said to occur to cause the change of the relationship among positions. A more directed root-cause search process can be then launched.

Now, we consider the variation component caused by the wafer difference within a batch. Let dw denote the difference between wafer readings:

$$dw_{j(i)} = X_{ij\bullet} - X_{i(j+1)\bullet} \qquad j = 1...m-1$$

T^2 control charts can be then constructed against dw's：

$$T^2_{(i)} = (dw_{(i)} - \overline{dw})' \, S_{dw}^{-1} \, (dw_{(i)} - \overline{dw})$$

Where $dw_{(i)}$ is the ith obersvation and is a $(m-1)$ò1 vector: [$d_{p1(i)}$ $d_{p2(i)}$ $d_{p3(i)}$ $d_{p4(i)}$]; $\overline{dw}$ is the average of dw's; and S_{dw} is the estimated covariance matrix of dw. The control limit (UCLw) becomes:

$$T^2_{m-1,r,\sim} = (r(m-1)/(r-m+2))*F_{m-1,r-m+2,\sim}.$$

Like the control charts for the positions, when the control limit is exceeded, a more directed root-cause search process and corrective action can be taken to tackle the problem causing the changes of the relationship among wafers within a same batch.

Finally, an $\overline{X}$ control chart can be constructed to monitor the effects of batches:

$$X_{i\bullet\bullet} = \sum_{j=1}^{m} \sum_{k=1}^{n} X_{ijk}.$$

The upper and lower control limits are:

$$UCLx = X_{\bullet\bullet\bullet} + k*\left(\frac{1}{r-1}\sum_{i=1}^{r}(X_{i\bullet\bullet} - X_{\bullet\bullet\bullet})^2\right)^{1/2} \text{ and}$$

$$LCLx = X_{\bullet\bullet\bullet} - k*\left(\frac{1}{r-1}\sum_{i=1}^{r}(X_{i\bullet\bullet} - X_{\bullet\bullet\bullet})^2\right)^{1/2},$$

respectively. Here, the control chart is used to detect any process excursion that causes the mean shift of the entire batch.

By using our approach, all variation sources have been taken into consideration and only 3 control charts are required to be constructed. In comparison, the conventional approaches do not consider correlation components and require to construct at least $n+m-1$ control charts.

3.2 Optimal allocation of critical inspection points

The following parameters are used to describe the multistage production process. n is the total number of production stages. P_k is the probability that an item is defective after going from stage 1 through stage k, where every process stage is assumed to be in statistical control. Since new defects may occur at every stage, $P_k >= P_l$ if $k > l$. The costs involved in the model are: I_k, unit inspection cost at stage k; U_k, unit scrap cost of defective items discarded at stage k; and C_d, penalty cost incurred for a defective finished product that is shipped out to customers.

The objective is to find at which production stage the inspection should be conducted such that the expected total cost is minimized. Instead of using the expected total cost, we here use the expected unit discovering/discarding cost, namely, the expected cost of discovering and discarding (ECDD) *one* defective item, as an intermediate objective function during the search process for the optimum solution. An alternative dynamic programming approach is derived based on this intermediate objective function. We will later show how this approach simplifies the solution searching process. Hereafter, we shall refer to this expected unit discovering/discarding cost as *unit ECDD*. Let D_k denote the unit ECDD at stage k with no removal of defective items at prior stages. We can express D_k as:

$$D_k = \frac{I_k}{P_{k-1}} + U_k . \qquad (1)$$

Suppose that l_1 is the first inspection point selected by comparing the unit ECDD among n stages. The comparison can be formulated as:

$$l_1 = \left\{ k : D_k = \min_{1\le i\le n}\{D_i\} \text{and } D_k < C_d \right\}. \qquad (2)$$

We continue the search for inspection points at stages subsequent to l_1. The problem is turned to which stage should be chosen as the second *potential* inspection point among the subsequent stages, i.e. stages $l_1 +1$ to n. Again, intuitively, we should choose the stage with a lowest unit ECDD. We already have the first chosen inspection stage at l_1. We are now required to calculate a *joint* unit ECDD with inspections performed at two stages: stage l_1 and a subsequent stage, say k.

$$D_{\{l,k\}} = \frac{P_{l_1-1}D_{l_1} + (1-P_{l_1-1})I_k + (P_{k-1} - P_{l_1-1})U_k}{P_{k-1}}$$

$$k \in \{l_1 +1, \ldots, n\} . \qquad (3)$$

To actually minimize the total discovering/discarding cost, we need to consider both the joint unit ECDD, with inspection points at stage l_1 and a subsequent stage, and the unit ECDD for a sole inspection point at one of the subsequent stages with no prior inspection performed at earlier stages. The following equation expresses this comparison:

$$T_{l_2} = \left\{ T_k : D_{T_k} = \min_{k\in\{l_1+1,n\}}\{D_{\{k\}}, D_{\{l_1,k\}}\} \text{and } D_{T_k} < C_d \right\} (4)$$

where T_{l_2} represents a set of one or two inspection points that minimizes the total ECDD up to this second chosen stage l_2. After choosing the second potential inspection point l_2 and its corresponding set of inspection points T_{l_2}, we may now skip stages between stage l_1 and stage l_2 and concentrate only on stages subsequent to l_2. The search for the third potential inspection point, as well as the forth, the fifth, etc, will follow the same procedure as in Equation (4).

Assume that the mth potential inspection point has reached stage l_m and the corresponding set of inspection points is T_{l_m}. Similar to Equation (3), the joint expected cost of discovering and discarding *one* defective item at a set of inspection points T_{l_m} and a subsequent stage k:

$$D_{\{T_{l_m},k\}} = \frac{P_{l_m-1}D_{\{T_{l_m}\}} + (1-P_{l_m-1})I_k + (P_{k-1} - P_{l_m-1})U_k}{P_{k-1}}$$

$$k \in \{l_m +1, \ldots, n\} \qquad (5)$$

We prove that we will be allowed to skip stages between l_m and l_{m+1}, if $T_{l_{m+1}}$ is chosen as follows:

$$T_{l_{m+1}} = \left\{ T_h : D_{T_h} = \min_{h\in\{l_m+1,n\}}\{D_{\{h\}}, \ldots, D_{\{T_{l_m},h\}}\} \text{ and } D_{T_h} < C_d \right\} \qquad (6)$$

Similarly, if expected costs of discovering and discarding *one* defective item at the remaining subsequent stages (after stage l_{m+1}) are all greater than the penalty cost C_d, then $T_{l_{m+1}}$ is the optimum solution. On the other hand, if costs less than the penalty cost can still be found among the remaining stages, the search process continues.

The total number of computations using the above program will be:

$$\sum_{i=0}^{m-1}(n-l_i). \qquad (7)$$

The saving in calculation efforts using this new dynamic programming approach can be clearly seen in the example given by Lindsay and Bishop (1964).

4. Conclusions

In this project, we have investigated the problems that arise when apply SPC techniques in a complex semiconductor manufacturing processes. An effective SPC chart construction strategy was proposed. In addition, a cost-effective strategy to allocate critical inspection points was also proposed. Both methodologies were not only proved to be mathematically sound but also shown to be quite effective. What was reported here is only a brief summary of our research results. Upon request and with the consent of NSC, we would be glad to provide the complete results to interested readers. Part of the research results has been published in an international journal.

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