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Grey Situation Decision-making Algorithm to Optimize Silicon Wafer Slicing

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ABSTRACT

The slicing of Silicon wafer is a complex manufacturing process in producing the raw materials for electronic chips and requires the efforts to effectively monitor the stability in production line and ensure the quality for the products composed of different shapes and materials. Human decision failure and other analytical errors are the most common source of management problems in such manufacturing stage. This paper presents a case regarding the silicon wafer manufacturing to examine the response to quality errors. The study has adopted the approach of grey situation decision-making algorithm for problem detection that suggests a technique to attain the quality control and reduce potential costs in production.

INTRODUCTION

Taiwanese information technology (IT) industry has acquired immense significance for its prominent role in contributing to the Taiwanese economy. One of the key elements in the Taiwanese IT industry is the production of Integrated Circuits (IC) which acts as the raw materials of computer devices, e. g., CPU, graphic adapter, network chips, etc. The supply chain of IC industry can be further divided into five segments, namely foundry wafer, IC package, IC fabrication, diode and transistor. The starting phase of IC production is the slicing of silicon wafer, which requires vacuum processing, crystallographic perfection, precise mechanical tolerances, and the monitoring of process stability and quality control for various sets of products. Despite the advent of cutting techniques in IC production, the difficulty in attaining the required precision in slicing of silicon wafer still remains. Generally, two scenarios incur damage on the work piece: (1) inaccurately estimating the precision of the slicing machine and (2) inconsistently controlling the wafer quality by applying the sampling method owing to the small batch size of wafer slices in the production model (Gopal & Rao, 2003). Given unstable yields of synchronously multiple quality characteristics are unstable or drifting accuracy of wire saw machines, consequently, there is a need to investigate solutions for employing machine control and monitoring measures by the production inspectors. To tackle the situation, extant literature (Gopal & Rao, 2004; Sreejith, et al., 2001) has suggests three synchronously occurring features of precision quality in wafer slicing, that they are thickness (THK), bow and warp to be simultaneously inspected using automatic testing equipment. Lin, et al. (2004) presented that in statistical methods, decision makers confront multi-variables by considering many samples and assuming that they obey some identified distribution to analyze and compare their relationships. In this study, the balance the costs and the benefits is concerned with a decision process as the solution of this particular case in the silicon wafer slicing. We present grey situation decision-making procedures can be appropriately used to reduce the sample size without knowing data. The main feature of the "grey situation decision method (GSDM)" is that it can be used with very few data and can use an arbitrary distribution of data to make an objective decision (Deng, 1999). Thus, the worst multiple abnormal quality characteristics can be screened from those sampling data without reducing the excellence of the whole process quality. Additionally, the EWMA control chart is used to demonstrate an on-line process that continues to monitor data to verify the effectiveness of using the GSDM in the wafer slicing manufacturing process.

METHODOLOGY

The grey system method, initiated by Deng (1989, 1999), has been widely applied to various fields including manufacturing processes. For example, Ma et al., (1996) applies grey decision making on vegetable production. Likewise, Hao and Cheng (1997) presents grey situation decision to the selection of aforementioned

station species. Wang, et al., (2001) decision matrix is proposed to construct GSDM processes. From another aspect, Lin, et al (2005) use grey relational analysis for the evaluation of digital video recorder system. This research proposes a combined method of GSDM and entropy approaches that are applied to screen the worst quality characteristic from the synchronously occurred multiple quality characteristics. The two approaches are discussed as following.

Grey Situation Decision-making

Grey situation decision-making provides a procedure to deal with one event that is associated with multiple scenarios and it facilitates the selecting process of the best or the worst situation. The definition and algorithm of the method are shown as below (Deng 1999; Hao and Cheng, 1997; Ma, et al., 1996; Wang, et al., 2001; Lin, et al., 2005).

Definition 1. Let S_{ij} = (a_i, b_j) = (Events, Games), and $a_i,\ i=1,\ 2,\ ...,\ m$ be the sample screening events and $b_j,\ j=1,\ 2,\ ...,\ n$ be the countermeasures of the multiple quality characteristics in the process.

Definition 2. If $S_{ij}=\left(a_i,\ b_j\right)$ is a situation, then the effectiveness of a_i and b_j can be written as E_{ij}. Let *M* be a mapping, $M\left(E_{ij}\right)=R_{ij}$, where R_{ij} is the value of the mapping. If *M* satisfies $M\left(E_{ij}\right)=R_{ij}\in R$, $R_{ij}\in\left[0,\ 1\right]$, then *M* can be referred to as the mapping effectiveness measurement. The properties of *M* are as follows.

(1) The upper-bound effective measuring target of *M* is "higher-the-better."

$$R_{ij}=\frac{E_{ij}}{\max\limits_{i}\ E_{ij}}. \qquad (1)$$

(2) The lower-bound effective measuring target of *M* is "lower-the-better."

$$R_{ij}=\frac{\min\limits_{i}\ E_{ij}}{E_{ij}}. \qquad (2)$$

(3) The moderate effective measuring target of *M* is "target-is-the-best."

$$R_{ij}=\frac{\min\limits_{i}\left\{E_{ij},\ E_0\right\}}{\max\limits_{i}\left\{E_{ij},\ E_0\right\}}, \qquad (3)$$

Where $E_0=\frac{1}{n}\sum_{i=1}^{n}E_{ij}$; *i* is the index of sample, and *j* is the index of the countermeasure for quality characteristics.

Definition 3. Let the situation, S_{ij}, has *i* measuring targets for the firm. If the mapping of E_{ij} is $M\left(E_{ij}\right)=R_{ij}$, then the synthetic measured effectiveness value, R_{ij}, for one of the event is,

$$R_{ij}^{\Sigma}=\sum_{j=1}^{n}w_jR_i\ . \qquad (4)$$

where *j* is the index of the countermeasure for quality characteristics. w_j is the weight of *j*-th entity (or quality characteristic). The weight, w_j, can be determined by the entropy measurement. The associated mapping synthetic effectiveness measuring vectors, R_i^{Σ}, exists and can be expressed as,

$$R_i^{\Sigma}=\left\{R_{i1}^{\Sigma},\ R_{i2}^{\Sigma},\ ...,\ R_{il}^{\Sigma}\right\}. \qquad (5)$$

Definition 4. If $R_{ij}^{\Sigma *}$ satisfies the following condition,

$$R_i^{\Sigma *}=\max\limits_{i}\ \left\{R_{ij}^{\Sigma}\right\},\quad \mathrm{i}\in I=\left\{1,\ 2,\ ...,\ m\right\}, \qquad (6)$$

where *m* is the index of sample data, then $S_{ij}^{*}=\left(a_i,\ b_j^{*}\right)$ are "satisfying situations"; b_j^{*} is the satisfied

countermeasure of the quality characteristic of sample screening event, a_i, and $R_i^{\Sigma *}$ is the best situation of the satisfactory situation.

Weights Determine by Entropy Measurement

To prescribe the relative priority among the synchronously occurred multiple quality features, a weight factor is given to each of them. Each weight of entity is evaluated using the concept of entropy proposed by Shannon and Weaver (Shannon & Weaver, 1959; Jee & Kang, 2000). The entropy E_j of the normalized values of a *j*-th entity is defined as follows:

$$E_j = -k \sum_{i=1}^{N} r_i(j) \log r_i(j). \qquad (7)$$

where E_j is in the range of 0 to 1; $r_i(j) = \frac{x_i(j)}{\sum_{i=1}^{N} x_i(j)}$, and $k = \frac{1}{\log N}$.

The weight w_j for the *j*-th entity is defined as:

$$w_j = \frac{1 - E_j}{\sum_{j=1}^{K} (1 - E_j)}. \qquad (8)$$

The GSDM and entropy methods of procedures to screen out the worst quality characteristic include seven steps.

Step 1: Sample five wafers randomly and measure their quality characteristics

Step 2: Determining situations, confirm targets and sample events

Step 3: Analyzing the samples

Step 4: Computing the entropy weight

Step 5: Making the GSDM decision

Step 6: Performing an EWMA control chart to verify the GSDM

CASE IMPLEMENTATION

Process Capability Analysis

Silicon wafer processes are constituted of crystal growing, pulling, slicing, lapping, etching, polishing, and cleaning. The measuring items of the process and parameter of quality control used in theses processes are: (1) lack of precision in thickness (THK), bow and warp caused by unstable motion of the wire knife and scrape mark during the slicing process and (2) quality control parameters, such as, electricity, resistivity and oxidation that relate to crystal pulling are not discussed in this paper. In the lapping process, the lapped wafer will be revised with those quality characteristics in item (1) by using precision lapping machines. However, the manufacturing cost of the lapping and polishing processes are much higher than that of the slicing process. Hence, quality control of slicing process mainly focuses on the unstable multiple quality characteristics.

Currently, the case firm only uses THK characteristic to control the slicing process. Figure 1 indicates the THK quality characteristic that inspecting an entire ingot can obtain 284 pieces and the parameter was set to 750±30(μ), THK variation and wire knife adjustment time. The average THK was 760.222(μ), while yield was 0.87 and the wire knife was adjusted 44 times. Whenever the wire knife was adjusted, the adjustment times appear (e.g.,

14th, 18th and 29th sliced wafers). Finally, with repeated wire knife adjustments, the adjusting times appear at the 72nd~75th, 126th ~132nd, 141st~143rd and 223rd~228th wafer slices.

Figure 1: Inspecting 284 Pieces of THK.

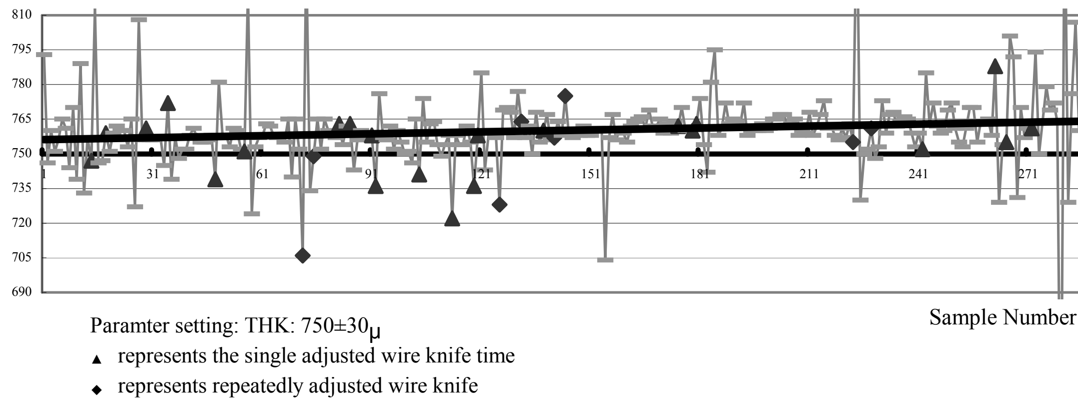


Table 1 displays the process capability of THK quality characteristics. Column 2 lists specifically the parameter of THK, 750±30μ. Clearly, C_{pL} = 1.128 is superior to C_{pU} = 0.555 and C_{pk} = 0.555, suggesting that slicing process capability is unstable. Nevertheless, the average THK for slicing is 760.222(μ), implying that the central line moves up by 10.222(μ). Column 3 displays the parameter for THK assuming a shift of the central line 10(μ) to 760(μ), with the C_{pk} index being recalculated as 0.738. On the contrary, C_{pU} and C_{pL} are stable and fixed. The right column displays the defective yield after adjusting the wire knife, while the C_{pk} index is recalculated as 1.084, consistent with the standard process capability, C_{pk} = 1.33. From the above analysis, the quality control department suggests that engineers should check these parameters. When the wire knife is adjusted, particularly, operators should deal with wafer slicing before moving the lapping process.

Table 1. Analysis of Process Capability THK.

Process Capability	Target Value		
	Customer Target (750μ)	Target Shift 10μ (760μ)	Take of Defective Wafer
Upper Process Capability (C_{pU})	0.555	0.756	1.122
Lower Process Capability (C_{pL})	1.128	0.738	1.084
Process Capability (C_{pk})	0.555	0.738	1.084

However, the slicing process actually accompanies with three multiple characteristics. Subsequently, the decision makers who used THK characteristic to monitor and control the slicing quality may lead to an unsuitable situation. Such unstableness of slicing process very often results from incorrect parameter setting by engineers or uncarefulness by the staff at production lines. In the next section, the GSDM method is also presented to screen the critical characteristics for monitoring and controlling the slicing quality.

Screening the Worst Quality Characteristic from Synchronously Occurring Multiple Quality Characteristics

Previous works consider repairable systems subject to random failures and analyse trade-offs between the costs and the benefits of maintenance activities (e.g., Bardey, et al. 2005). Based on a revised approach of the GSDM model, the six steps adapted in this case. The steps of GSMD method to screen the worst quality characteristic in the IC slicing process are as following:

Step 1. Sample five 6-inch work-pieces randomly and measure their quality characteristics

To sample five 6-inch work-pieces whose samples have been completely confirmed randomly, measuring the multiple quality characteristics at five points on each work-piece; then averaging the measured data within the

range of these points (See Table 2).

Table 2. Measured Multiple Quality Characteristics of wafer. (Unit:μ).

Quality Characteristics	Work-pieces of Sample				
	1	2	3	4	5
THK	789.00	744.00	759.00	753.00	752.00
Warp	26.60	20.80	27.00	22.80	21.90
Bow	10.90	16.80	15.95	16.05	16.70

Step 2. Determining situations, confirm targets and sample events

Finding upon the situations in order to confirm the targets and sample events.

(1) Event: decide the screening samples of the quality characteristics, and can be defined as a_1.

(2) Countermeasure quality characteristic 1, THK (defined as b_1); quality characteristic 2, warp (defined as b_2); quality characteristics 3, bow (defined as b_3).

(3) Situation:

$S_{11} = (a_1,\ b_1)$ = (sample screening of the quality characteristics; countermeasure for quality characteristic 1).

In S_{ij}, *i* is the index of the sample; *j* is the index of the quality characteristics.

$S_{12} = (a_1,\ b_2)$ = (sample screening of the quality characteristics; countermeasure for quality characteristic 2);

$S_{13} = (a_1,\ b_3)$ = (sample screening of the quality characteristics; countermeasure for characteristic 3);

(4) Target:

Target 1: THK is the target-is-the-best effective measured value, and

$E_{11} = 789,\ E_{21} = 744,\ E_{31} = 759,\ E_{41} = 753,\ E_{51} = 752$.

Target 2: Warp is the lower-the-better effective measured value, and

$E_{12} = 26.6,\ E_{22} = 20.8,\ E_{32} = 27.0,\ E_{42} = 22.8,\ E_{52} = 21.9$.

Target 3: Bow is the lower-the-better effective measured value, and

$E_{13} = 10.9,\ E_{23} = 16.8,\ E_{33} = 15.95,\ E_{43} = 16.05,\ E_{53} = 16.7$.

Step 3. Analyzing the samples

Measuring the samples, according to (4) in Step 2, THK, warp and bow are the target-is-the-best, lower-the-better, and lower-the-better quality characteristics, respectively. Use Eq. (3) to compute the effective measured value of THK and Use Eq. (2) to compute the effective measured value of warp and bow. Table 3 lists the dimensionless linear normalization.

Step 4. Computing the entropy weight

To compute entropy weight of every quality characteristic by using Eqs. (7) and Eqs. (8) and the results are tabulated in Table 4.

Table 3. Data Normalization.

Quality Characteristics	Work-pieces of Sample				
	1	2	3	4	5
THK	0.9625	0.9797	0.9995	0.9916	0.9903
Warp	0.7820	1	0.7704	0.9123	0.9498
Bow	1	0.6488	0.6834	0.6791	0.6527

Table 4. Entropy Weights, w_j, of Samples.

Sample	1	2	3	4	5
Weights (w_j)	0.158087	0.150899	0.154447	0.380339	0.156229

Step 5. Making the GSDM decision

Eq. (4) yields the synthetic effective measured value, $R_{11}^{\Sigma}=0.9862$ $R_{12}^{\Sigma}=0.8889$ and $R_{13}^{\Sigma}=0.7218$. Thus, the worst quality characteristic is bow. Bow is therefore monitored. However, the firm currently monitors the THK quality characteristic. The synthesized effective measured values of THK are the highest. Therefore, the process capability of THK is very stable and the manufacturer need not spend much money or time to inspect and monitor this characteristic.

Step 6. Performing an EWMA control chart to verify the GSDM

At this stage, the effective measured value of bow, warp and THK are plotted on an EWMA chart. The EWMA chart is modeled as (Lucas and Saccussi, 1992; Robert, 1959),

$$Z_t=\lambda \overline{X}_t+\left(1-\lambda\right)Z_{t-1},\quad t=1,\ 2,\ ...,\ n, \qquad (9)$$

whereλis the weighting factor (defined by the decision maker) and typical values for λ are between 0.05 and 0.3 in statistical process control applications; $\overline{X}_t$ is the subgroup average for the current subgroup at time *t* (or the current observation if the subgroup size is one ($n=1$)); the value of *Z* at time zero, Z_0, is either a target value or the overall average of the selected subgroups (also defined by the decision maker).

The upper and lower control limits for the EWMA statistics are as follows.

$$UCL=Z_0+\frac{3\sigma}{\sqrt{n}}\sqrt{\left(\frac{\lambda}{1-\lambda}\right)\left(1-\left(1-\lambda\right)^{2i}\right)}, \text{ and} \qquad (10)$$

$$LCL=Z_0-\frac{3\sigma}{\sqrt{n}}\sqrt{\left(\frac{\lambda}{1-\lambda}\right)\left(1-\left(1-\lambda\right)^{2i}\right)}, \qquad (11)$$

where *i* is the observation time, Z_0 is the starting value (defined by the decision maker as either the target value or the process mean value), and *n* is the size of the subgroup.

The process standard deviation, σ, is estimated using the $\overline{X}$ chart and setting $\lambda=0.3$ and $n=2$ to monitor and inspect bow, warp and THK. The EWMA control chart is used to demonstrate an on-line process that continues to monitor 124 data to verify the effectiveness of using the grey situation decision method in the wafer slicing manufacturing process (Nong et al., 2002). Effective measured value of bow, warp and THK are plotted on an EWMA chart. On this chart, 124 samples are generated while the process is controlled. Figure 2 shows an upper bound of the bow's EWMA chart by $\overline{X}$ counts, Figure 3 shows the warp and Figure 4 shows the THK. In Figures 2 to 4 (i.e. bow, warp and THK), the same out-of-control conditions appear at about 28th the signals. In Figure 2, the out-of-control signals start from the 6th $\overline{X}$ count, but in Figure 4 the $\overline{X}$ count of THK is under control. In consequence, the quality of bow ought to be monitored more frequently than the quality of THK. Therefore, the effectiveness of monitoring the worst characteristic, bow, using an EWMA control chart is the same as that of using our decision process method. That is, bow dominates other characteristics.

Figure 2. Upper Side of Bow's EWMA Chart by $\overline{X}$ Counts.

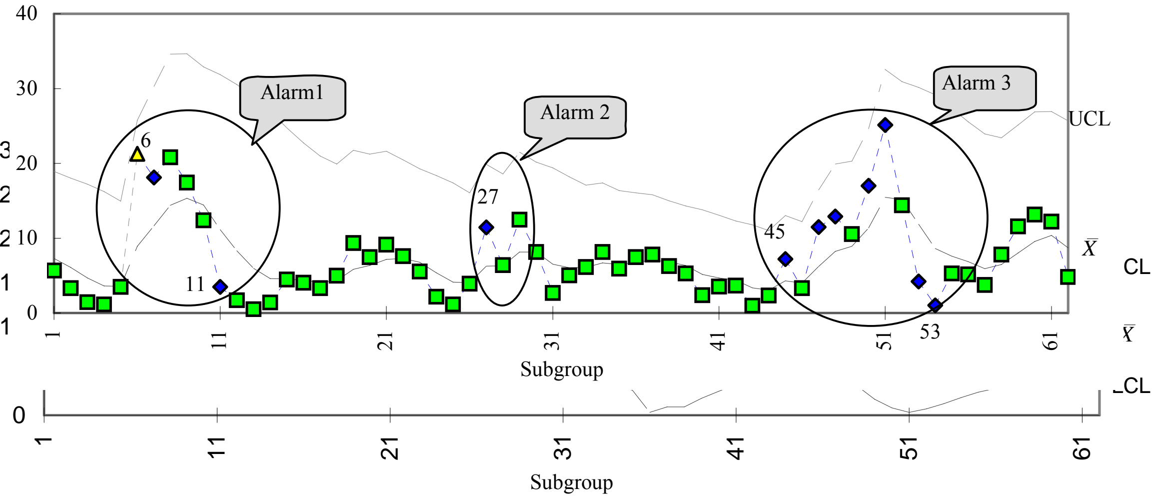
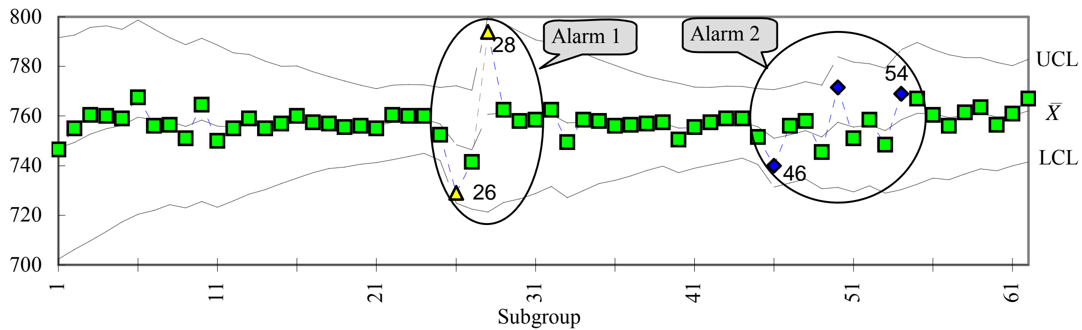


Figure 4. THK's EWMA Chart by $\overline{X}$ Counts.



In summary The EWMA control chart is used to monitor bow, warp and THK quality characteristics, by taking 124 observations during slicing to confirm the results estimated by the GSDM method. Bow is the worst quality characteristic in the slicing process. THK is the best quality characteristic. Nevertheless, the firm's inspection and monitoring of THK is not appropriate. Mistakes of engineers and operators are the most frequent causes of low yields and instability of slicing process.

The decision steps discussed above lays a basis of further applications for the manufacturing problem diagnosis and production quality control. It is a feasible solution for practitioners to reduce potential costs and better decision-makings in the manufacturing of IC products and can be applied to other type of products by sequential manufacturing procedures.

CONCLUSION

In the slicing process, multiple quality characteristic problems arise from uncertain and imprecise data. The method of entropy and GSDM is adequate to deal with these problems. This study has suggested the entropy method to compute objective weight and amend GSDM to support the needs of computing synthetic effective means. Thereby, decision makers are able to apply the procedures to screen the worst quality characteristic form synchronously occurring abnormalities multiple quality characteristics. The main contribution of this paper is that it provides the opportunities for industrial practitioners to screen out the worst quality characteristic from existing quality characteristics in the slicing process with fewer samples (such as in this research, only five historical samples are adopted).

The foregoing sections with the computed results yield the following conclusions. (1) Bow is the worst quality characteristic in the slicing process. Although THK is the best quality characteristic, notwithstanding, the firm's inspection and monitoring of THK is not appropriate. (2) The EWMA control chart is used to monitor THK, bow and wrap quality characteristics, by taking 124 observations during slicing to confirm the results using the GSDM. The effectiveness of monitoring using the EWMA control chart is the same as that obtained using the GSDM. (3) The firm should use the proposed technique to improve their control of the quality of wafers.

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