Measuring Manufacturing Yield for Gold Bumping Processes Under Dynamic Variance Change

W. L. Pearn, Y. T. Tai, and W. L. Chiang

***Abstract*—Recently, the technology of gold bumping has become more popular due to high demand for LCD driver ICs. The requirement of higher resolution application, however, will increase the difficulties for manufacturing the gold bumps due to their high pin counts. For gold bumping processes, bump height is one of the key parameters to control process yield. In reality, some inevitable process variations and shifts regarding the bump height may occur under dynamic manufacturing environment. Conventionally, manufacturing yield for gold bumping processes is calculated under the assumption that the processes are stable. In practice, however, the processes are dynamic, particularly, in the operation of Au-plating in gold bumping factories. To obtain accurate measure of the manufacturing yield, we present a capability index method for manufacturing yield calculation with dynamic variance change considerations. Using this method, the magnitude of the undetected variance change, which is function of the detection power of the S^2 chart, is incorporated into the adjusted calculation of manufacturing yield. The detection powers of the S^2 chart under various subgroup sizes are tabulated. For illustration purposes, a real application in a gold bumping factory which is located in the Science-based Industrial Park in Hsinchu, Taiwan, is presented.**

***Index Terms*—Gold bumping, dynamic variance change, manufacturing stability control, manufacturing yield.**

I. Introduction

WITH increasing demand on higher resolution display in portable devices, such as mobile phones, personal digital assistants (PDAs), and digital cameras, the demand of precision process on display-related components have become more and more critical. Take TFT-LCD driver ICs for examples, the driver ICs of HVGA (Half Video Graphics Array, 320 RGB $\times$ 480) resolution need 1440 pads on OLB (outer lead bonding) side and around 200 pads on ILB (inner lead bonding) side. Totally, it has 1640 pads in limited space, as depicted in Fig. 1. Therefore, in contrast with the conventional package technology, the chip-on-glass (COG) process has been developed to mount the driver ICs upon the glass substrates directly. The key technology of driver ICs mounting on a glass substrate is through the thermal compression method [1]. In the thermal compression process, it needs precise height of gold bump to achieve high resolution display. In the case of some pads with un-uniform gold bump heights should induce malfunction of display. Hence, to control the process stability for bump height, we provide an accurate measurement of manufacturing yield for the essential parameter in the gold bumping process.

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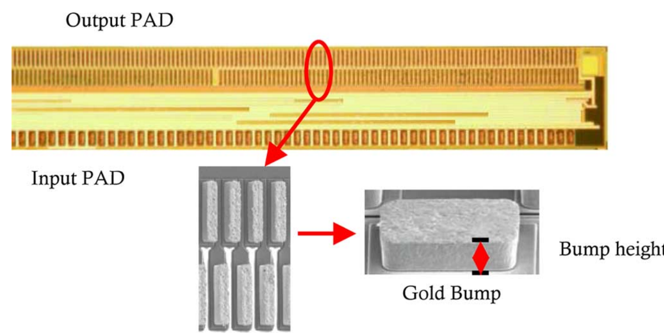

Fig. 1. Diagram of a driver IC.

In the gold bumping process, bump height is the height between the top of bump and the top of pad. As mentioned above, bump height is one of the critical parameters to control process yield. Choi *et al.* [2] mentioned that the bump height variation was an important factor since it increased the probability of the open failure. To avoid the results of uneven bump height, process engineers involved in gold bumping shop floors should control the process parameter carefully. However, some inevitable process variations and shifts exist in the dynamic manufacturing environment. The variations or shifts may arise from equipments, human, and manufacturing processes. Conventionally, practitioners usually employ charts to monitor the manufacturing stability and apply capability indices to evaluate the manufacturing yield and establish the relationship between the actual performance and the manufacturing specifications.

Unfortunately, a chart will not detect every movement in the process mean and variance [3]. Furthermore, a basic assumption for the calculation of manufacturing yield applying typical capability indices is that the process is stable. However, no process is ever truly stable, especially in the dynamic gold bumping manufacturing process. For this reason, an approach for measuring manufacturing yield with dynamic variance change considerations is provided in this paper. The calculation of yield under dynamic conditions increases the accuracy of yield and further helps those practitioners to obtain a more precise evaluation for the manufacturing stability and yield control.

This paper is organized as follows. The yield control problem for the gold bumping process is first identified in Section II. Then, Section III provides a capability index method for calculating manufacturing yield under the dynamic environment. In Section IV, to demonstrate the applicability of the method of

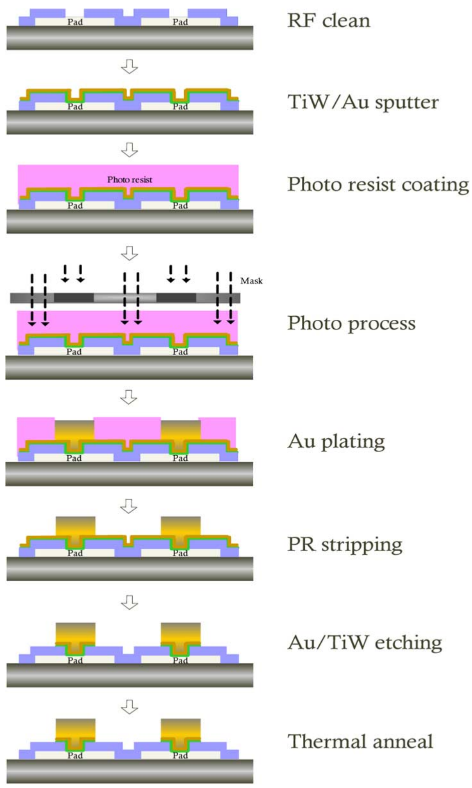

Fig. 2. Gold bump process flow.

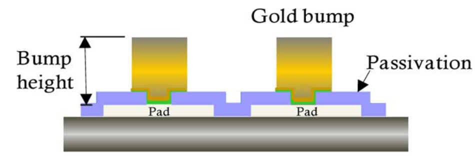

Fig. 3. Bump cross section configuration.

yield calculation, we consider two real-world applications taken from a gold bumping factory which is located in the Science-based Industrial Park in Hsinchu, Taiwan. Finally, Section V provides the conclusions.

II. Gold Bumping Manufacturing Yield Problem

Recently, the technology of gold bumping has become more popular due to high demand for LCD driver ICs. Gold bumping utilizes thin film deposition, photolithography, and electroplating processes to form gold bumps on pads. Generally, the detailed process of gold bumping involves eight major operations: 1) RF clean; 2) TiW/Au sputter; 3) photo resist (PR) coating; 4) photo process; 5) Au plating; 6) PR stripping; 7) Au/TiW etching; and 8) thermal anneal, as shown in Fig. 2. In operation 1, after the RF cleaning process, the flux residues on the surface of un-sawed wafers should be removed. For operation 2 and 3, TiW/Au is sputtered on the wafer and photo resist is also coated. In operation 4, the photolithography process, after UV exposure, the pattern is formed. Next, in operation 5, Au is plated on the area where PR is not covered. Furthermore, in operation 6 and 7, the PR is stripped and Au/TiW is etched, respectively. Finally, in operation 8, through the thermal anneal, the hardness of gold bump can be decided.

The gold bumping manufacturing is very essential process that affects the production yield of the COG interconnection technology. In gold bumping factories, process yield is currently defined as the percentage of processed product unit passing inspection. That is, the product characteristic must fall within the manufacturing tolerance. However, the requirements of higher resolution applications will increase the difficulties of manufacturing the gold bumps due to their high pin counts. In the case of HVGA (Half Video Graphics Array, 320 RGB $\times$ 480) resolution, it needs 1640 pads in a same chip, including 1440 pads on OLB side and 200 pads on ILB side, typically. Any pad of these 1640 pads with shorter or higher bump height would induce open failure while mounting the driver IC onto a glass substrate. Hence, to obtain a satisfactory yield on gold bumping process, the parameter of bump height is a key factor and should be well-controlled. The bump cross section configuration is shown as Fig. 3.

However, the control of the parameter of bump height is complicated due to three critical reasons, which are addressed as follows. First, due to increasing cost of gold, the specification of bump height has been requested to become shorter than before. Owing to the limitations of equipment for the gold bumping process, it is more difficult to control the variation of bump height while shrinking it. Second, in the operation of Au-plating, it is hard to control the deposit rate while forming the gold bumps on a 200-mm wafer. The deposit rate in the wafer center may be different from the rate in the wafer edge which results in the variation of bump height. It becomes more serious while gold bumps should be formed on a 300-mm wafer. Thirdly, due to past experience of gold bumping process, the hard bumps can increase the probability of anisotropic conductive film (ACF) conductive particles being fractured. After ACF is fractured, it becomes conductive to connect IC pads with ITO-electrode on glass [4]. However, the variation of bump height may easily arise from hard bumps. A higher bump in a chip may block another shorter bump to be connected with ITO-electrode on glass. Hence, controlling the parameter of bump height becomes important in the common COG mounting process.

III. Capability Index Approach for Calculating the Manufacturing Yield

Process yield has been the most basic and common criterion used in the manufacturing industry for measuring process performance. Due to fiercer competition in the global TFT-LCD industry, the manufacturing yield of gold bumping processes demands very low fraction of defectives, normally measured by parts per million (ppm) or parts per billion (ppb). Consequently, the accuracy of calculating manufacturing yield becomes essential; as it could provide feedback to engineers on what actions need to take for manufacturing yield control and improvement. If the process parameter is out of control and detected, some improvement actions must be initiated immediately.

For gold bumping manufacturing, the product characteristic must fall within the specification tolerance. For nonconforming product units, additional costs would incur for scrapping or

TABLE I
NONCONFORMING UNITS IN PPM VERSUS CAPABILITY INDEX

C_{pk}	Yield	Non-conformities (ppm)
1.0	0.997300204	2699.796
1.1	0.999033152	966.848
1.2	0.999681783	318.217
1.3	0.999903807	96.193
1.4	0.999973309	26.692
1.5	0.999993205	6.795
1.6	0.999998413	1.587
1.7	0.999999660	0.340
1.8	0.999999933	0.067
1.9	0.999999988	0.012
2.0	0.999999998	0.002

repairing. However, conforming product units are accepted without these additional rework costs. During the last decade, capability index C_{pk} has been widely used to measure manufacturing yield in gold bumping factories but assuming that the process is under stable condition. However, the deposit rate in the operation of Au-plating and the hardness of bump significantly affect the stability of the gold bumping process. That is, the manufacturing process is dynamic and the process variance of bump height could change. In this paper, we present a capability index approach under dynamic variance change conditions for calculating the manufacturing yield.

A. Gold Bumping Yield Calculation Under Stable Condition

Capability index C_{pk} is originally proposed by Kane [7], which is defined as $\min\{(USL-\mu)/3\sigma, (\mu-LSL)3\sigma\}$, where UCL and LSL are the upper and lower specification limits, respectively; μ is the process mean and σ represents the process standard deviation. Applying the C_{pk} capability index requires that the process is under stable condition and the manufacturing yield measure is based on the assumption that the process output follows normal distribution [8]. Table I displays various commonly used capability requirements and the corresponding process yields associated with NCPPM (non-conformities in parts per million).

B. Gold Bumping Yield Calculation Under Dynamic Condition

Due to the process limitation regarding the deposit rate in the operation of Au-plating and the requirement of hard bump, the process variance of bump height often change and the manufacturing condition is under such dynamic environment. Consequently, to measure the manufacturing yield more accurately, the variance change of bump height must be considered. Bothe [3] investigated normally distributed processes with dynamic mean shift. Hsu *et al.* [9] investigated the problem when manufacturing data follows Gamma distributions. To date, no research has been conducted on calculating the manufacturing yield under the condition with dynamic variance change. Incorrect manufacturing yield calculation misleads the practitioners to overestimate the performance of their manufacturing processes. To consider and incorporate the process variance change, we propose a modified yield calculation method to handle the dynamic variance change problem.

In the shop floor of gold bumping, to control the manufacturing stability, the S^2 chart, which is introduced by Shewhart [10], is usually employed to monitor the process center and spread. However, using the S^2 chart, small change of variance is rather difficult to be detected due to the limitation of its detection power. Unfortunately, the variance change does affect the calculation of the gold bumping manufacturing yield which is an essential criterion related to the process control. We first investigate the detection power of the S^2 chart. We then propose a modified yield calculation method to incorporate the magnitude of the undetected small variance change.

TABLE II
DETECTION POWER OF THE S^2 CHART FOR NORMALLY DISTRIBUTED PROCESSES WITH VARIOUS SAMPLE SUBGROUP SIZES

n	variance change size ($k\sigma$)					
	$k=1.0$	$k=1.5$	$k=2.0$	$k=2.5$	$k=3.0$	$k=3.5$
10	0.00270	0.21103	0.66071	0.88802	0.96388	0.98766
11	0.00270	0.23550	0.70680	0.91592	0.97636	0.99289
12	0.00270	0.26014	0.74771	0.93727	0.98465	0.99594
13	0.00270	0.28486	0.78377	0.95346	0.99009	0.99769
14	0.00270	0.30956	0.81536	0.96565	0.99365	0.99870
15	0.00270	0.33417	0.84288	0.97477	0.99595	0.99927
16	0.00270	0.35861	0.86673	0.98155	0.99743	0.99959
17	0.00270	0.38281	0.88730	0.98656	0.99838	0.99978
18	0.00270	0.40671	0.90497	0.99025	0.99898	0.99988
19	0.00270	0.43026	0.92009	0.99296	0.99936	0.99993
20	0.00270	0.45340	0.93297	0.99493	0.99960	0.99996

1) Detection Power of S^2 Chart for Manufacturing Stability Control: Steps for calculating the probabilities for catching different size of variance change for various sample subgroup sizes n of the S^2 chart are presented in the following.

Step 1) Calculate the control limit of the S^2 chart.
The upper control limit is $UCL = (\bar{S}^2/n-1)\chi^2_{0.00135,n-1}$, the center line is $\bar{S}^2$, and lower control limit is $LCL = (\bar{S}^2/n-1)\chi^2_{0.99865,n-1}$, where $\chi^2_{0.00135,n-1}$ and $\chi^2_{0.99865,n-1}$ denote the 0.00135 and 0.99865 percentage points of the chi-square distribution with $n-1$ degrees of freedom, noting that the $\bar{S}^2$ is the average sample variance obtained from the analysis of preliminary data.

Step 2) Calculate the detection power for the S^2 chart.
If σ changes to another value $k\sigma_0$ (variance change), the probability of detecting this change (detection power) can be calculated as follows:

$$\begin{aligned}&\text{Detection power}\\&\quad= 1-\beta\\&\quad= 1-P\left(LCL \le S^2 \le UCL | \sigma=\sigma_1=k\sigma_0\right)\\&\quad= 1-P\left(\int_{LCL}^{UCL} f(u=s^2)du | \sigma=\sigma_1=k\sigma_0\right)\end{aligned}$$

where $f(u)$ denotes the sampling distribution of the sample variance and σ_1 is the new standard deviation after the variance change (σ_0 is the standard deviation of the original process).

Table II displays the detection power for various magnitude of variance change for normal process with various sample subgroup sizes $n = 10(1)20$. For the S^2 chart with sample subgroup size $n=10$, when the variance change size is greater than $2\sigma_0$, it has about 66.1% chance to detect the change. However,

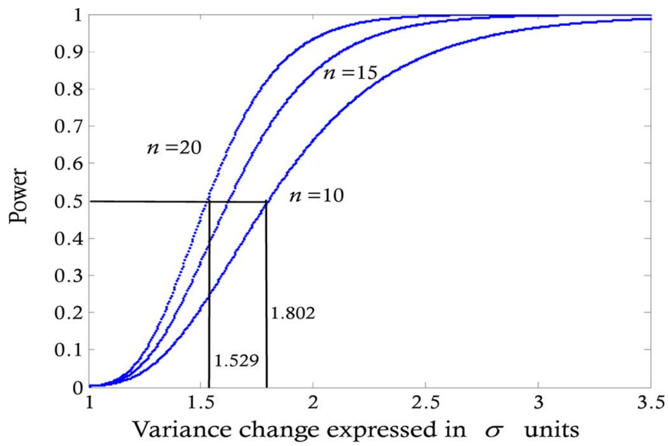

Fig. 4. Power curves of S^2 chart for sample subgroup sizes 10, 15, and 20.

TABLE III
AS_{power} VALUES OF S^2 CHART FOR VARIOUS SAMPLE SUBGROUP SIZES

n	Power=0.5	n	Power=0.5	n	Power=0.5
10	1.80215	17	1.58119	24	1.47696
11	1.75533	18	1.56210	25	1.46611
12	1.71577	19	1.54480	26	1.45595
13	1.68158	20	1.52901	27	1.44647
14	1.65192	21	1.51445	28	1.43755
15	1.62555	22	1.50099	29	1.42903
16	1.60220	23	1.48849	30	1.42107

the chance of catching a $1.5\sigma_0$ variance change would decrease to 21.1%. Such low probabilities indicate that small changes of variance may not be detected.

Fig. 4 plots the probabilities displayed in Table II, with each curve for a different sample subgroup size. Those power curves portray the chances of detecting different size of changes in variance change (expressed in σ units on the horizontal axis). We note that for very small variance change, the power curves are close to zero (low detection power). On the other hand, the three detection power curves leveling off close to 100% when the size of the variance changes exceed 3.5σ. The horizontal line in Fig. 4 shows that there is a 50% chance of not catching a 1.529σ change in variance when n is 20, and missing the catch of 1.802σ change when n is 10.

To circumvent the undetected variance change causing the incorrect manufacturing yield calculation, AS_{power} is introduced. The notation AS_{power} is the magnitude of variance change we need to accommodate based on the designated detection power. We develop a Matlab program to compute the AS_{power} by setting the desired detection power and the sample subgroup size n. In general, $n = 10 \sim 30$ are the subgroups size commonly used in the industry. We set the detection power $= 0.5$ and $n = 10(1)30$. The magnitude of $AS_{0.5}$ computed based on the S^2 chart is displayed in Table III. From Table III, we can see that changes in σ smaller than $AS_{\text{power}}\sigma$ would likely be missed. Therefore, σ would be the marginal size of the undetected variance change we should accommodate.

2) Manufacturing Yield Calculation: Since variance change ranging from 0 up to $AS_{\text{power}}\sigma$ cannot be detected by the chart and overestimation of the manufacturing yield may give incorrect feedback to the process control, the optimal approach is to simply accommodate any variance change no greater than $AS_{\text{power}}\sigma$. When yield is calculated via the capability index under dynamic environment, the AS_{power} must be incorporated into the capability assessment formula. Consequently, the new capability formula can be rewritten as $\min\{(USL - \hat{\mu})/(3\hat{\sigma} \times AS_{\text{power}}), (\hat{\mu} - LSL)/(3\hat{\sigma} \times AS_{\text{power}})\}$. Using the new formula, the calculation of manufacturing yield will be more accurate. The more accurate manufacturing yield, therefore, can be expressed as $2\Phi\{3 \times \{\min[(USL - \hat{\mu})/(3\hat{\sigma} \times AS_{\text{power}}), (\hat{\mu} - LSL)/(3\hat{\sigma} \times AS_{\text{power}})]\}\} - 1$.

C. Discussions and Extensions

In the previous section, we present the more accurate yield calculation to circumvent the undetected variance change based on various designated detection power of the S^2 chart assuming the data come from normally distributed data. However, in some gold bumping factories, S chart is also employed for the manufacturing stability control. Further, in many cases, data come from general distributions rather than the normal distribution. In the following, we discuss two extensions to deal with those problems.

1) Using S Chart for Manufacturing Stability Control: Setting up and operating the S charts requires the same steps as those for the S^2 chart, except that for each sample we must calculate the sample standard deviation S and $\bar{S} = (1/m)\sum_{i=1}^{m} S_i$. In the first step, the control limits are constructed. Since the statistic $\bar{S}/c_4$ is an unbiased estimator of σ, the parameters of the S chart would be $UCL = B_4\bar{S}$, center line is $\bar{S}$, and $LCL = B_3\bar{S}$, where the constants $B_3 = 1 - (3/c_4)\sqrt{1 - c_{4^2}}$ and $B_4 = 1 + (3/c_4)\sqrt{1 - c_{4^2}}$. In the second step, we calculate the detection power for the S chart.

If the variance changes from σ_0 value to another value $k\sigma_0$, the probability of detecting this change (detection power) can be expressed as follows:

$$
\begin{aligned}
&\text{Detection power}\\
&\quad = 1 - \beta\\
&\quad = 1 - P\left(LCL \le S \le UCL | \sigma = \sigma_1 = k\sigma_0\right)\\
&\quad = 1 - P\left(\int_{LCL}^{UCL} f(v = s)dv | \sigma = \sigma_1 = k\sigma_0\right)
\end{aligned}
$$

where $f(v)$ denotes the probability density function of the sample standard deviation and σ_1 is the standard deviation after variance change (σ_0 is the standard deviation of the original process).

We also develop a Matlab program to compute the AS_{power} by setting the desired detection power and the sample subgroup size n. We set the detection power $= 0.5$ and $n = 10(1)30$, the magnitude of $AS_{0.5}$ based on the S chart is displayed in Table IV. From Table IV, we see that when the detection power is set to 0.5 and n is 15, the value of AS_{power} is equal to 1.610.

2) Manufacturing Yield for Generally Distributed Processes: Cases of generally distributed processes sometimes may also occur in gold bumping factories. Rinne [11] mentioned that Weibull distribution, together with the normal, exponential, χ^2, t, and F distributions, are the most popular models in modern

TABLE IV
AS_{power} VALUES OF S CHART FOR VARIOUS SAMPLE SUBGROUP SIZES

n	Power=0.5	*n*	Power=0.5	*n*	Power=0.5
10	1.78265	17	1.56705	24	1.46597
11	1.73679	18	1.54865	25	1.45547
12	1.69806	19	1.53175	26	1.44565
13	1.66483	20	1.51637	27	1.43645
14	1.63585	21	1.50237	28	1.42780
15	1.61031	22	1.48932	29	1.41956
16	1.58751	23	1.47723	30	1.41187

statistics. A Weibull distribution can cover a wide class of general applications. This distribution is utmost interest not only to theory-orientated statisticians because of its great number of special features but also to practitioners because of its ability to fit the data from various fields. For this reason, we consider the capability index method for the yield calculation under variance change with Weibull-distributed gold bumping data.

It should be pointed out that the explicit close forms regarding the probabilities of detecting variance change using the S^2 chart are rather complicated for Weibull-distributed data. To avoid overestimating process capability, we suggest the power of the S^2 chart for Weibull-distributed data based on the UCL and LCL be obtained using the simulation technique. The Type II error β is

$$\begin{aligned}\beta &= P\left(LCL \le S^2 \le UCL|\sigma_1 = k\sigma_0\right)\\ &= P\left(F_{0.00135} \le S^2 \le F_{0.99865}|\sigma_1 = k\sigma_0\right)\\ &= G_{S^2}\left(F_{0.99865}\right) - G_{S^2}\left(F_{0.00135}\right)\end{aligned}$$

where $1-\beta$ is the detection power of the process, $G_{S^2}(\cdot)$ is the empirical cumulative distribution function (CDF) of the sample variance from the Weibull distribution with new changed variance, and σ_1 is the standard deviation after process change (σ_0 is the standard deviation of the original process). The control limits LCL and UCL are calculated as $F_{0.00135}$ and $F_{0.99865}$, respectively. For the yield calculation, AS_{power} is incorporated into the calculation and the corresponding yield can be obtained. We particularly note that it can be proved, mathematically, that the calculation of AS_{power} would not be affected by the scale parameter of the Weibull distribution. We also note that for Weibull-distributed gold bumping processes, the dynamic manufacturing yield formula becomes

$$C_{pk} = \min\left\{\frac{F_{0.5} - LSL}{AS_{\text{power}}(F_{0.5} - F_{0.00135})}, \frac{USL - F_{0.5}}{AS_{\text{power}}(F_{0.99865} - F_{0.5})}\right\}$$

where $F_{0.00135}$, $F_{0.5}$, and $F_{0.99865}$ are the percentile points of the CDF of the Weibull-distributed gold bumping process.

IV. GOLD BUMPING MANUFACTURING YIELD CALCULATION

In this section, we consider two real-world applications taken from a gold bumping factory located in the Science-based Industrial Park at Hsinchu, Taiwan, to demonstrate the applicability of the proposed method. For the example investigated, we consider the product type of HV7850B, which belongs to HVGA (320 RGB $\times$ 480) product series. As mentioned above, there are thousands of pads in the same chip, the pin counts are so high that it is necessary to monitor the manufacturing stability of the bump height. The inspection data are commonly collected from the shop floor. Generally, they are obtained from specific slot numbers of wafers in one lot, specific die sites in one wafer, and specific bump sites in one die via some designate sampling plans. In the gold bumping factory, it has typically 25 pieces of wafers in a lot. Each wafer has its corresponding number ranging from 01 to 25. Five die sites are inspected on a wafer at the location of top, center, bottom, left, and right, which is depicted as Fig. 5. Further, four bump sites are checked on one die where their corresponding sites are referred to as Top-L, Top-R, Down-L, and Down-R, respectively.

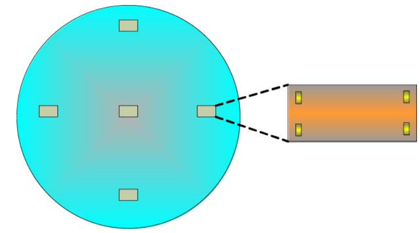

Fig. 5. Testing sites in one wafer and one die.

TABLE V
THE 100 INSPECTION DATA OF BUMP HEIGHT (UNIT: μm)

12.30	12.31	11.76	12.25	12.25	12.41	11.91	12.25	12.44	12.19
11.89	11.33	12.03	12.31	12.09	12.45	11.66	12.17	12.01	11.90
12.27	11.69	12.58	12.06	12.00	12.18	12.44	11.68	11.60	12.78
11.73	12.43	12.08	12.38	12.50	12.48	11.86	11.98	12.09	12.88
12.12	12.05	12.49	12.84	12.70	12.00	12.09	11.78	12.11	11.63
11.44	12.21	11.86	12.26	11.92	12.05	12.09	11.71	12.19	12.67
11.93	12.40	12.09	12.09	12.12	11.68	12.01	11.76	12.25	12.20
12.24	11.40	11.84	12.39	11.83	11.55	12.22	11.96	12.51	11.73
11.99	11.68	12.28	12.11	12.31	11.86	12.00	12.15	11.91	12.29
12.49	11.86	12.01	11.73	11.32	12.18	11.55	12.05	12.17	12.63

To illustrate the use of the capability index to measure process yield under variance change, we present two cases which are randomly sampled from the inspected data in the shop floor. Table V displays the 100 inspection data of the bump height in the first case for HV7850B. The μ is used as the unit for the specification of bump height.

The specifications on bump height for the HV7850B product are 14, 12, and 10 μm for USL, *Target*, and LSL, respectively. Fig. 6 shows that the plotted points fall approximately along a straight line which implies that the distribution of observations of the bump height can be said as normally distributed. Furthermore, Fig. 7 indicates the shape of the histogram, which also indicates that the distribution of the bump height is approximately normal distribution. Therefore, we could consider the application of S^2 case for normal distributions and use the formulas developed for the normal distributions.

The parameters μ and σ of this case could be calculated from the historical data, giving $\hat{\mu} = 12.086$ and $\hat{\sigma} = 0.327$. Conventionally, C_{pk} is calculated as $C_{pk} = \min\{(USL - \hat{\mu})/3\hat{\sigma}, (\hat{\mu} - LSL)/3\hat{\sigma}\} = \min\{(14 - 12.086)/3(0.327), (12.086 - 10)/3(0.327)\} = \min\{1.951, 2.126\} = 1.951$ under the assumption of stable

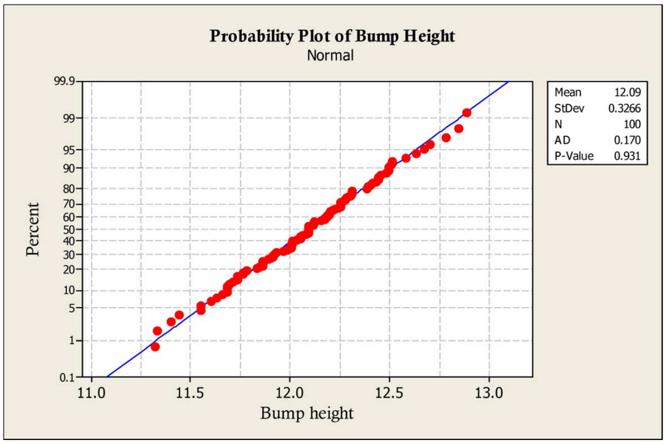

Fig. 6. Normal probability plot of the historical data.

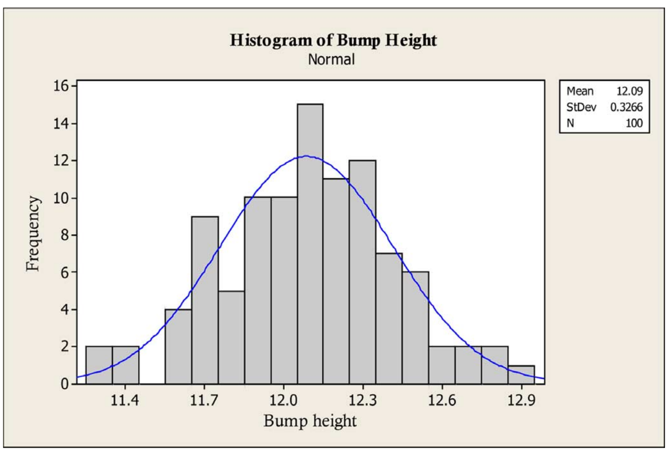

Fig. 7. Histogram plot of the historical data.

variance. Using the dynamic formula to cover undetected change in variance; however, the calculation of capability would be different ($AS_{0.5}$ of the S^2 chart is 1.466 when $n = 25$). The dynamic C_{pk} is calculated in the following:

$$\begin{aligned}&\text{Dynamic } C_{pk}\\&= \min\left\{\frac{USL-\hat{\mu}}{3\hat{\sigma}\times AS_{\text{power}}}, \frac{\hat{\mu}-LSL}{3\hat{\sigma}\times AS_{\text{power}}}\right\}\\&= \min\left\{\frac{14-12.086}{3(0.327)(1.466)}, \frac{12.086-10}{3(0.327)(1.466)}\right\}\\&= \min\{1.331, 1.450\} = 1.331\end{aligned}$$

The value of the dynamic C_{pk} reflects the real situations more closely due to the consideration of the variance change. Obviously, when the sample subgroup size n is increased, a change in σ has a higher probability to be detected. For example, if n is 30, the value of $AS_{0.5}$ would be 1.421 and dynamic $C_{pk} = \min\{(USL-\hat{\mu})/(3\hat{\sigma}\times AS_{\text{power}}), (\hat{\mu}-LSL)/(3\hat{\sigma}\times AS_{\text{power}})\} = \min\{(14-12.086)/3(0.327)(1.421), (12.086-10)/3(0.327)(1.421)\} = \min\{1.373, 1.496\} = 1.373$. Changing the sample subgroup size n from 25 to 30 increases the value of dynamic C_{pk} index value from 1.331 to 1.373. The values of corresponding manufacturing yields are 99.993% and 99.996% when $n = 25$ and $n = 30$, respectively.

For the other case, the calculated parameters μ and σ of size 100 with normally distributed data are $\hat{\mu} = 12.175$ and $\hat{\sigma} = 0.298$. The calculated value of the conventional C_{pk} is 2.041. If the $AS_{0.5}$ is incorporated and the dynamic C_{pk} formula is applied, the values of the dynamic C_{pk} index are 1.392 and 1.437 and the values of production yield are 99.997% and 99.999% for sample subgroup size $n = 25$ and $n = 30$, respectively. In the conventional capability index method, the industrial applications do not consider variance change, and consequently, the manufacturing yields would be overestimated. Using our method, the yield can be calculated more accurately.

V. Conclusion

The gold bumping manufacturing is an essential process that affects the production yield of the COG interconnection technology. To produce high-resolution portable products, the requirement of high pin count IC chips would increase the difficulties of manufacturing the gold bumps due to high demand on uniformity. In gold bumping factories, bump height is a critical parameter for maintaining high-level of the manufacturing yield. The basic assumptions of all conventional methods have ignored the fact that the variance of bump height may change. Incorrect calculation of the manufacturing yield would lead to overestimate their stringent requirement on the manufacturing yields. In this paper, we presented a capability index method to calculate the manufacturing yield incorporating the factor of variance change. To demonstrate the applicability of the proposed calculation method, we considered two real-world gold bumping shop floor applications taken from the factory located in the Science-based Industrial Park at Hsinchu, Taiwan. The computational results showed that changing the sample subgroup sizes n, different values of capability indices would be obtained. Consequently, the corresponding more accurate manufacturing yields can be obtained. The proposed manufacturing yield calculation based on the capability index method under dynamic variance change could be used as a reference point for obtaining the realistic process performance. The results obtained could also help the practitioners to make more reliable decisions on what actions need to take in controlling their gold bumping manufacturing processes.

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