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ORIGINAL ARTICLE

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Manufacturing performance evaluation for IC products

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Abstract As we known, the product diversity and complexity in the production line will gradually increase. When the multiple products were alternately produced at the same line, the manufacturing performance will be difficult to evaluate. In particular, traditional process capability analysis and related process capability indexes cannot be directly employed to the IC manufacturing process. As we know, the yield has a direct effect on the manufacturing cost. Hence, yield is frequently used by most IC manufacturers to evaluate manufacturing performance. The diversity of function will become another analytic consideration due to that the component density, wafer area and product complexity of an IC product rapidly increase. Hence, the diversity of function can be regarded as the evaluated factor. Additionally, the defects on a wafer will begin to cluster as the wafer area gradually increases. Therefore, only using the yield to represent manufacturing performance may not lead to an appropriate judgment. In particular, only using the yield to evaluate the process's stability and the product's maturity can not provide a meaningful resolution. The primary reason is that the inherent features in the processes or products are not included into analyzing. For instance, even though the defect count, defect size and defect distribution are the same, the yield loss of the complicate manufactured product will be less than that of the simple manufactured product. In this study, we propose a simple performance evaluation index to assess the manufacturing performance in the IC manufacturing industry. This evaluation index is constructed according to a modified Poisson yield model, and the related parameters regarding the process or product (e.g., the minimum linewidth, the area of a die, the number of manufactured process or layer, the degree of defect clustering, and so on.) are taken into consideration. In addition, an integrated evaluation procedure is also suggested to evaluate the performance of the manufacturing of multiple IC products. According to the result obtained from the illustrative example, the index and the procedure can overcome the drawback of separately using yield or defect count in the analysis. The rationality and the feasibility of the proposed evaluated index and the procedure can be verified by demonstrating the illustrative example.

Keywords Integrated circuit (IC) · Manufacturing performance · Yield analysis · Yield model

1 Introduction

As we known, the product diversity and complexity in the production line will gradually increase. When the multiple products were alternately produced at the same line, the manufacturing performance will be difficult to evaluate. In particular, traditional process capability analysis and the related process capability indexes cannot be directly used to monitor the IC manufacturing process. As we known, yield is an important measure to evaluate manufacturing performance in the IC industry. The yield has a direct effect on the manufacturing cost. Hence, it is frequently regarded as an index to measure IC manufacturing performance. Basically, the IC manufacturers with a higher yield will be the manufacturers that have a higher competitive power and higher product quality. Therefore, the degree of manufacturing performance and the maturity of an IC product can be assessed by using yield analysis. The results derived from yield analysis can provide useful information about process improvement and product design. In addition, the price of a product and manufacturing strategy can be accurately determined using yield analysis. Therefore, many IC manufacturers focus on enhancing their yield. Generally, the yield of an IC product can be represented by [1]:

$$Y_{\mathrm{overall}} = Y_{\mathrm{line}} \times Y_{\mathrm{die}} \times Y_{\mathrm{assembly}} \times Y_{\mathrm{final\_test}} \times Y_{\mathrm{quality}} \tag{1}$$

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where Y_{overall} is the overall yield of the IC product, Y_{line} is the line yield, Y_{die} is the die yield, Y_{assembly} is the assembling yield, $Y_{\text{final\_test}}$ is the final testing yield, and Y_{quality} is the quality yield. Among those yields, the die yield (Y_{die}) is more difficult to be determined than others. The primary reason is that it has a direct effect on productivity. Therefore, Y_{die} can be regarded as a primary factor having a direct effect on manufacturing cost. A reviewing of related research reveals that Y_{die} is frequently mentioned. In this study, the Y_{die} is also the "yield" we mention.

Generally, performance will be affected by the defect (or failure) on a wafer in IC manufacturing. There are many studies to address defect analysis. However, in this study, the type of defect is not the major consideration. The related content about the theory of defects will be explained well in [2]. The defect count or defect density can be viewed as another index to evaluate the manufacturing performance. However, defect clustering gradually occurs as wafer area increases. The yield analysis is more complicated since the relationship between the defect clustering and the yield must be considered. Hence, only applying the defect count or defect density to analyze the manufacturing performance will be not enough. Additionally, the manufacturing techniques in the IC industry are developing rapidly. According to Moore's law, the computation capability of the computer will double every eighteen months. The component density, wafer area, and product complexity of an IC product will quickly increase. The diversity of functions will gradually increase and become another area of concern. Therefore, only applying yield to represent the manufacturing performance may lead to a biased judgment. The primary reason is that the inherent features in the processes or products are not included into analyzing. For instance, even though the defect count, defect size and defect distribution are the same, the yield loss of the complicate manufactured product will be less than that of the simple manufactured product. After reviewing the possible drawbacks mentioned, we will propose an integrated procedure to evaluate the manufacturing performance based on a modified Poisson yield model. In particular, a performance evaluation index will be developed in this study.

The rest of this paper is organized as follows. Section 2 reviews several important yield models including their theory, limitations, and applications. Subsequently, Sect. 3 systematically describes the integrated procedure and performance evaluation index we developed. Section 4 provides an illustrative case from a semiconductor manufacturer in Taiwan's Science-Based Park to demonstrate the effectiveness of the proposed approach. Concluding remarks will be made in Sect. 5.

2 Related literature on yield models

The definition of yield (i.e., the die yield) is a ratio of the normal dies to the total dies on a wafer. In other words, yield can be regarded as the probability of producing a normal die. Hence, the yield model will have a functional relationship between yield, the process parameters, and the product parameters. Until now, several classifications of yield models have been developed. Among them, the composite yield model and the layered yield model are frequently mentioned [3]. The concept of the composite yield model is to apply the composite chip and the average defect count to predict the yield. As for the layered yield model, the yield is regarded as the product of each layer (i.e., the process) during the entire manufacturing procedure. The details of these two models are given as follows.

2.1 Composite yield model

The binomial yield model and Poisson yield model are two yield models initially developed in the IC manufacturing industry. The characteristic of the defect spatial distribution for a poisson model has proved to be an important consideration in this study. Poisson yield model is constructed according to the assumption that the defect on a die will obey the Poisson probability distribution and has independent relationship with respect to the other defects. Hence, the defect density and average defect can be considered constant. According to this concept, the probability value of a die with k defects can be formulated as follows:

$$P(K) = e^{-\lambda_0} \lambda_0^k / k!, \quad k = 0, 1, 2, \ldots \tag{2}$$

where λ_0 denotes the average defect count on a die – that is, it is the product of the averaged defect density (D_0) and the area of the die (A). Hence, the Poisson yield model can be defined as follows:

$$\text{Yield } = P(k = 0) = e^{-\lambda_0} = e^{-AD_0} \tag{3}$$

The Poisson yield model can reasonably estimate the yield when the area of the die is less than $0.25\,\text{cm}^2$. However, it will underestimate yield when the area of the die becomes larger [1]. The primary reason is that the size of the defect cluster is frequently bigger than the die area, and the change of defect density between different dies will be kept a fixed value. However, the defect density will significantly change as the die area becomes larger. Murphy [4] was the first researcher to find that defect density is not a fixed value. During his research, he recognized that the defect density D should be a random variable and it should obey the probability distribution $f(D)$. He proposed a probability density function, and that the probability value of a die with k defects can be defined as:

$$P(X = k) = \int_0^\infty \frac{e^{-\lambda} \lambda^k}{k!} f(\lambda)\,\mathrm{d}\lambda,$$

$$\text{or } P(X = k) = \int_0^\infty \frac{e^{-AD} (AD)^k}{k!} f(D)\,\mathrm{d}D \tag{4}$$

According to Eq. 4, the yield model can be formulated as follows:

$$\text{Yield } = P(X = 0) = \int_0^\infty e^{-AD} f(D)\,\mathrm{d}D = E(e^{-AD}) \tag{5}$$

However, Murphy suggested the normal distribution as the appropriate distribution to describe $f(D)$. Unfortunately, the computation using the normal distribution is more complicated. Therefore, he initially replaced it with a triangular distribution. Next, he assumed $f(D)$ to be uniformly distributed, and he compared the effect on yield using different values of $f(D)$. Finally, two yield models are derived and they are formulated as follows:

$$\text{Yield } = \left(\frac{1-e^{-AD_0}}{AD_0}\right)^2 \tag{6}$$

$$\text{Yield } = \frac{1-e^{-2AD_0}}{2AD_0} \tag{7}$$

where $D_0 = E(D)$.

After Eq. 5 was developed by Murphy, the focus of the development of a yield model had shifted to a search for an appropriate distribution of $f(D)$. The resulting model is called a compound Poisson yield model, and $f(D)$ is called a compounder [5]. If the compounder is replaced by the Gamma function, the derived model will be recognized as a negative binomial yield model [6]:

$$\text{Yield } = \left(1+\frac{AD_0}{\alpha}\right)^{-\alpha} \tag{8}$$

In the negative binomial yield model, changing the shape parameter (or cluster parameter) α $(1 < \alpha < \infty)$ can create different yield models. The flexibility of this model will provide the capability to explain different degrees of defect clustering. As for the model's application, it can be applied to predict yield, determine redundant circuits in an IC product, find the optimum zone split, and so on. However, if we use the actual die area to estimate yield based on the negative binomial model, we will underestimate the yield. Therefore, we should replace the actual area by the critical area. The reason is that not all defects will lead to yield loss [7].

2.2 Layered yield model

The primary concept of the layered yield model is that no matter what type of model is being used, the yield is the product of every layered yield. Herein, a layer will be denoted as a process or a mask. Therefore, the summation of the average defect count for every layer will be equal to the average of the entire defect count [3]:

$$\lambda = \sum_{i=1}^{N} \lambda_i, \quad N \text{ denotes the number of layer} \tag{9}$$

Two meanings are included in accord with such a concept:

1. If the layered yield model is applied to estimate yield, the assumed yield model will obey the assumption that the yield equals the product of every layered yield. Otherwise, the yield model is not accurate.
2. The defect count is a dimensionless value and it can be represented as a cardinal number.

According to the first meaning mentioned, only the Poisson yield model can satisfy such a constraint. However, the result derived from related research showed that the Poisson yield model will underestimate the actual yield. Ferris-Prabhu [3, 8] found the derived procedure for determining average defect count to be inappropriate. Next, he proposed a scaling rule to overcome this shortcoming. The concept of a scaling rule is to replace the average defect count by the average defect count of the reference product. The model is called the modified Poisson yield model.

2.3 Modified Poisson yield model

A product called the "reference product", which obeys the Poisson yield model, is assumed to be given initially. In addition, the related parameters of the product or process are also given at the same time. Then, the yield model for a new product can be constructed by choosing an overall scale factor σ as in Eq. 10 below:

$$Y = e^{-\lambda} = e^{-\sigma\lambda_e} = e^{-\sigma D_e A_e} = Y_e^{\sigma} \tag{10}$$

where λ denotes the average defect count for a new product, and λ_e, D_e, and A_e denote the average defect count, average defect density, and area of the die, respectively, for the reference product. The overall scale factor σ consists of the area scale factor α, sensitivity scale factor ψ, and complexity scale factor ξ. These three scale factors are explained as follows:

(1) area scale factor, α. To show the effect of average defect count on the case of a gradually increasing die area, Ferris-Prabhu proposed the area scale factor to deal with such a situation. The area scale factor can be formulated as follows :

$$\alpha = \left(\frac{A}{A_e}\right)^{1-b} \tag{11}$$

where A denotes the die area of the predicted product, and Φ_e denotes the die area of the reference product.

(2) sensitivity scale factor, ψ. The sensitivity of an IC product will affect the failure count. That is, there is a positive relationship between the degree of sensitivity and the probability of failure. Hence, the definition of sensitivity is the ratio of the failure of a predicted product and the failure of a reference product. It can be formulated as follows:

$$\psi = \frac{\Phi}{\Phi_e} \cong \left(\frac{w_e}{w}\right)^{p-1} \tag{12}$$

where Φ denotes the failure probability of the predicted product, Φ_e denotes the failure probability of the reference product, w denotes the linewidth of predicted product, w_e denotes the linewidth of the reference product.

(3) complexity scale factor, ξ. The degree of the complexity of an IC product will affect the total number of failures. The proba-

bility of producing more defects has a positive relationship with the complexity of the product. However, the complexity of the product is difficult to measure objectively. Hence, engineering experience is frequently employed to assign a reasonable value for complexity scale factor. Generally, the feasible range of this value is from 0.9 to 1.1 [8]. Finally, for a constant number of layers, the overall scaling factor can be formulated as follows:

$$\sigma = \alpha \times \psi \times \xi = \xi \times \left(\frac{A}{A_e}\right)^{1-b} \times \left(\frac{w_e}{w}\right)^{p-1} \tag{13}$$

When the number of layers is different, the overall scaling factor is given by:

$$\sigma = \xi \times \left(\frac{N}{N_e}\right) \times \left(\frac{A}{A_e}\right)^{1-b} \times \left(\frac{w_e}{w}\right)^{p-1} \tag{14}$$

where N denotes the number of layers, ξ is an objective value included in the error term.

2.4 Defect clustering

The IC manufacturing process frequently includes hundreds of procedures, such as alignment, lithography, etch, deposition, doping, etc. As the complexity of a process gradually increases, defects are inevitably produced on the wafer surface. Sometimes, these defects will lead to a faulty die and will significantly reduce the entire yield. Consequently, the number of defects is a significant factor in analyzing the wafer yield. However, Stapper [9, 10] reported that a wafer's defects tend to cluster. This clustering phenomenon becomes more evident as the wafer size increases. Thus, the resolution of the defect clustering is an important issue for IC yield analysis. Stapper [9, 10] recognized the degree of defect clustering as a significant factor affecting the IC yield and quality. Before judging the defect clustering, the distribution of the defects on a wafer should be addressed. Two methods are commonly used to analyze the distribution of sample points on a surface: the quadrat method and distance method [12]. The quadrat method divides the surface area into random or contiguous quadrats of the same size. Since selecting random quadrats affects the judgment of the distribution of points on a surface, contiguous quadrats are used herein to analyze the samples. By using the points in a quadrat as a sample, the mean and variance can be calculated for all of the samples. Consequently, a t-test statistic developed by Greig-Smith [11] can be determined as follows:

$$t = \frac{\frac{V}{M} - 1}{\sqrt{\frac{2}{n-1}}} \tag{15}$$

where V denotes the variance, M denotes the mean, and n denotes the number of squares, respectively. The t-test statistic will follow a t-distribution with $(n-1)$ degrees of freedom. If the t value exceeds the critical value $t_{(\alpha,n-1)}$, then the distribution of points on the surface is not random, i.e., the points tend to cluster. The larger the t value, the more serious the defect clustering. In other words, we can employ the ratio of variance and mean to be the evaluation index to represent the degree of defect clustering.

3 Performance evaluation index and evaluation procedure

Before developing the evaluating procedure, we initially assume that n different products are collected. Among these n products, at least one product can be chosen as the reference product. In addition, the related parameters of the process or product and yield can be given. Next, we set two conditions for choosing the candidate of the reference product:

1. It is a mature IC product: this means the product or the process is in a stable manufacturing state.
2. It is an IC product with a smaller die area: a die are of less than 0.25 cm^2 is necessary to satisfy the Poisson model.

Under these two assumptions, the yield model of the reference product will be formulated as $Y_e = e^{-\lambda_e}$; that is, the average defect count can be represented as follows:

$$\lambda_e = -\ln Y_e \tag{16}$$

Next, we will use the n data points to obtain the estimate of the overall scaling factor in the modified Poisson model. In other words, we can derive the overall scaling factor as Eq. 18 according to Eq. 10. According to Eq. 9, we can derive the overall scaling factor as follows:

$$\sigma = \frac{-\ln Y}{\lambda_e} = \frac{-\ln Y}{D_e A_e} \tag{17}$$

The overall scaling factor can be regarded as a function of related parameters such as the number of layers, the die area, and the linewidth. Although the b value in the area scaling factor (see Eq. 11) can represent the defect clustering (0 denotes no defect clustering and 1 denotes critical defect clustering), we cannot directly choose an appropriate value in practice. Therefore, we simplify the meaning of the area scaling factor and take another clustering scaling factor into consideration. According to the historical record and engineers' experience, the relationship between the degree of defect clustering and the yield is indeterminate. Hence, two relationships (both positive and negative correlation) should be taken into consideration. After integrating all concepts mentioned, the overall scaling factor can be formulated in a more meaningful way (see Eqs. 18 and 19 below).

Case 1: positive correlation

$$\sigma = f\left(\frac{N}{N_e}, \frac{A}{A_e}, \frac{W_e}{W}, \frac{\frac{V}{M}}{(\frac{V}{M})_e}\right) \tag{18}$$

Case 2: negative correlation

$$\sigma = f\left(\frac{N}{N_e}, \frac{A}{A_e}, \frac{W_e}{W}, \frac{(\frac{V}{M})_e}{\frac{V}{M}}\right) \tag{19}$$

If we integrate Eqs. 16, 17, 18, and 19, the estimated overall scaling factor can be described by Eqs. 20 and 21:

$$\sigma = -\frac{\ln(Y)}{\lambda_e} = f\left(\frac{N}{N_e}, \frac{A}{A_e}, \frac{W_e}{W}, \frac{\frac{V}{M}}{\left(\frac{V}{M}\right)_e}\right) \tag{20}$$

$$\sigma = -\frac{\ln(Y)}{\lambda_e} = f\left(\frac{N}{N_e}, \frac{A}{A_e}, \frac{W_e}{W}, \frac{\left(\frac{V}{M}\right)_e}{\frac{V}{M}}\right) \tag{21}$$

We can then employ the regression analysis method to construct the function model. After obtaining the regression model, the estimate of the overall scaling factor can be computed. Next, the estimated yield can be computed by $Y_i = e^{-\hat{\sigma}_i A_e D_e}$, where i denotes the ith product. The entire derived procedure is graphically depicted in Fig. 1.

The defect status should keep stable when the production line reminder a stable status. If the yield of producing the ith product is Y_i, the corresponding defect density RD_i can be defined as follows:

$$RD_i = \frac{-\ln Y_i}{\sigma_i A_e} \tag{22}$$

If the production line which having produced the i-th product to produce the reference product will be viewed as the necessary condition, the meaning of RDi can be explained as the average value of defect density when producing the reference product.

Finally, the performance evaluation index (PEI) for producing multiple products can be formulated as follows:

$$PEI_i = (D_e / RD_i) \tag{23}$$

This PEI is a relative index to evaluate manufacturing performance. It can transfer the representation of producing different products into the representation of producing the same reference product. Therefore, we can represent the relative grade between the actual manufacturing performance and the expected level by using the proposed PEI.

The meaning of the proposed PEI can be explained as follows:

1. $PEI_i > 1$ means that the manufacturing performance of manufacturing product i is better than the expected level. The larger the PEI_i, the better the manufacturing performance.
2. $PEI_i = 1$ means that the manufacturing performance of manufacturing product i is just at the expected level.
3. $PEI_i < 1$ means that the manufacturing performance of manufacturing product i is worse than the expected level. The smaller the PEI_i, the worse the manufacturing performance. That is, the process needs to be improved.

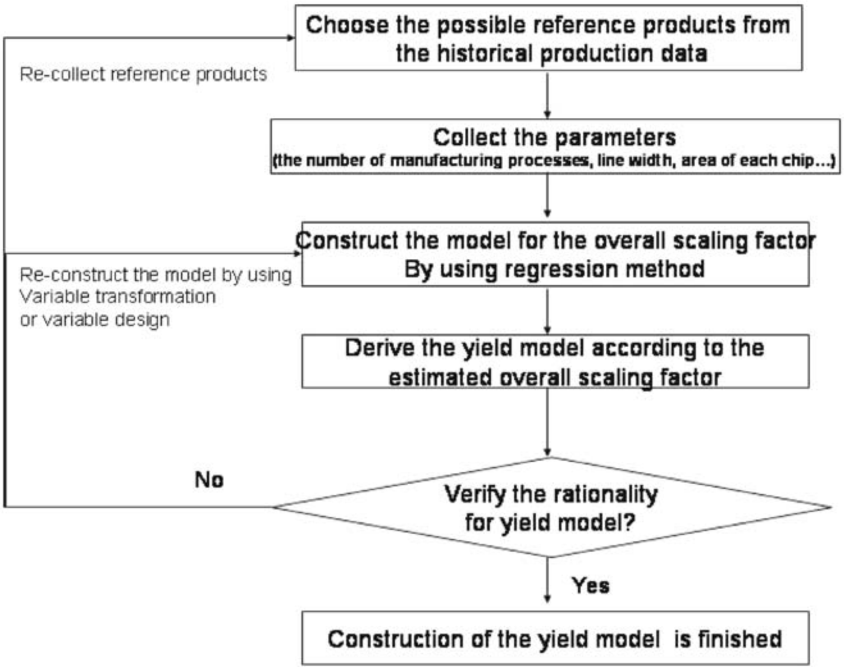
Next, we will construct an integrated procedure for evaluating the manufacturing performance as follows:

Step 1: Construct the yield model database (DB).
Such a DB will include related information such as the number of layers, the minimum linewidth, the die area, the degree of defect clustering, and so on. The information will be collected from the historical production record with a stable process and a mature product. The information can be also provided by experienced engineers.

Step 2: Choose a possible product to be a candidate for the reference product and compute the corresponding average defect count.

Step 3: The regression analysis method will be employed to fit the model of the overall scaling factor. Next, the parameters in the modified Poisson yield model will be

Fig. 1. The constructed procedure of the yield model



estimated and the appropriate yield model with respect to the product can be constructed.

Step 4: Use the fitted model's R^2 value to choose the appropriate reference product with the maximum R^2 value.

Step 5: Compute the performance evaluation index PEI_i according to the chosen reference product and draw a conclusion with respect to PEI_i.

4 Experimental example

An experimental example from a semiconductor manufacturer in Taiwan's Science-Based Park is employed to demonstrate the proposed approach. Two IC products are manufactured, and the manufacturer wishes to realize a certain manufacturing performance. The engineers collect the related information during about six months and they are as follows:

IC-1. the average yield is about 70%, the minimum linewidth is 0.15 µm, the number of layers is 16, the area of the die is $0.158\,\text{cm}^2$, and the average degree of defect clustering (V/M) computed in the manufacturing line is 5.325;

IC-2. the average yield is about 65%, the minimum linewidth is 0.18 µm, the number of layers is 15, the area of the die is $0.184\,\text{cm}^2$, and the average degree of defect clustering (V/M) computed in the manufacturing line is 3.835; From such information, we cannot directly determine which product has the better performance. In addition, we cannot provide any conclusion regarding the product's maturity or the process's stability. Hence, we will employ the proposed procedure in Sect. 3 to resolve it step by step.

Step 1: Firstly, we construct the yield model DB. After a discussion with a well-experienced senior engineer, we choose about 25 IC products from the historical record with better stability and higher maturity (where the defect clustering has been corrected during process improvement). The yield model DB will consist of several parameters including the minimum linewidth, the number of masks (or layers), the area of the die, the average degree of defect clustering and the average yield of lots. They are listed in Table 1 (due to proprietary considerations, the listed data were transformed).

Step 2: According to the decision criterion, three products are chosen to be possible reference products (the criterion is to choose the product with die area less than $0.25\,\text{cm}^2$). Next, the average defect count of each product can be computed as:

$$\lambda_e = -\ln(Y_e) = 0.1601688 \text{ (for IC-A)}$$
$$\lambda_e = -\ln(Y_e) = 0.1911605 \text{ (for IC-B)}$$
$$\lambda_e = -\ln(Y_e) = 0.1031408 \text{ (for IC-C)}$$

Step 3: Construct a linear regression model.

3-1 For IC-A

Firstly, we assume IC-A has a positive correlation (it will be denoted as IC-A-P) with the degree of defect clustering and yield.

In this step, the regression analysis method is used. The dependent variable is the overall scaling factor σ and the independents variable are (N_i/N_e), (A_i/A_e) (w_e/w_i), and $((V/M)/(V/M)_e)$. The number of data points is 24, because the data of IC-A are not included to perform model fitting. The fitted linear regression model is given by:

$$\hat{\sigma}_i = -1.04124 + 1.229215 \times \left(\frac{N_i}{N_e}\right) + 0.185442 \times \left(\frac{A_i}{A_e}\right) + 0.229928 \times \left(\frac{w_e}{w_i}\right) - 0.13118 \left(\frac{\left(\frac{V}{M}\right)_i}{\left(\frac{V}{M}\right)_e}\right) \tag{24}$$

where $R^2 = 0.83277$. Finally, the constructed yield model is $Y_i = e^{-0.1601688\sigma_i}$.

Secondly, we assume IC-A has a negative correlation (it will be denoted as IC-A-N) with the degree of defect clustering and yield.

In this step, the regression analysis method is used. The dependent variable is the overall scaling factor σ and the independent variables are (N_i/N_e), (A_i/A_e) (w_e/w_i), and $((V/M)_e/(V/M))$. The number of data points is 24, because the data of IC-A are

Table 1. The attributes of the yield model DB

Datum	The minimum linewidth (µm)	The number of masks (layers)	The area of the die (cm^2)	The degree of defect clustering (V/M)*	Yield (%)**
1	L	N	A	D	Y
2	L-0.2	N+2	A+0.0865	D+0.0744	Y-6.3
3	L+0.2	N	A+0.1262	D-0.0274	Y+2.8
...					
23	L-0.5	N+5	A+0.3342	D+0.3852	Y-12.3
24	L	N+2	A+0.2735	D+0.2867	Y-8.6
25	L-0.5	N+5	A+0.1035	D+0.1294	Y-12.8

*Denotes the average degree of defect clustering
**Denotes the average yield of lots

not included to perform model fitting. The fitted linear regression model is given by:

$$\hat{\sigma}_i = -1.47117 + 1.228176 \times \left(\frac{N_i}{N_e}\right) + 0.18713 \times \left(\frac{A_i}{A_e}\right) + 0.24244 \times \left(\frac{w_e}{w_i}\right) + 0.29122 \left(\frac{\left(\frac{V}{M}\right)_e}{\left(\frac{V}{M}\right)_i}\right) \tag{25}$$

where $R^2 = 0.833853$. Finally, the constructed yield model is also $Y_i = e^{-0.1601688\sigma_i}$.

3-2 For IC-B

Firstly, we assume IC-B has a positive correlation (it will be denoted as IC-B-P) with the degree of defect clustering and yield.

The dependent variable and the independent variable are the same as for IC-A. The number of data points is 24, as the data of IC-B are not included to perform model fitting. The fitted linear regression model is given by:

$$\hat{\sigma}_i = 0.014255 + 0.146403 \times \left(\frac{N_i}{N_e}\right) + 0.333708 \times \left(\frac{A_i}{A_e}\right) + 0.553511 \times \left(\frac{w_e}{w_i}\right) - 0.13531 \left(\frac{\left(\frac{V}{M}\right)_i}{\left(\frac{V}{M}\right)_e}\right) \tag{26}$$

where $R^2 = 0.8168$. Finally, the constructed yield model is $Y_i = e^{-0.1911605\sigma_i}$.

Secondly, we assume IC-B has a negative correlation (it will be denoted as IC-B-N) with the degree of defect clustering and yield.

The dependent variable and the independent variable are the same as for IC-A. The number of data points is 24, as the data of IC-B are not included to perform model fitting. The fitted linear regression model is given by:

$$\hat{\sigma}_i = -0.42196 + 0.15637 \times \left(\frac{N_i}{N_e}\right) + 0.3376 \times \left(\frac{A_i}{A_e}\right) + 0.56492 \times \left(\frac{w_e}{w_i}\right) + 0.28244 \left(\frac{\frac{V}{M}e}{\frac{V}{M}i}\right) \tag{27}$$

where $R^2 = 0.818157$. Finally, the constructed yield model is $Y_i = e^{-0.1911605\sigma_i}$.

3-3 For IC-C

Firstly, we assume IC-C has a positive correlation (it will be denoted as IC-C-P) with the degree of defect clustering and yield.

The dependent variable and the independent variable are the same as for IC-A and IC-B. The number of data points is 24, as the data of IC-C are not included to perform model fitting. The fitted linear regression model is given by:

$$\hat{\sigma}_i = 0.58064 + -0.07767 \times \left(\frac{N_i}{N_e}\right) + 0.4439 \times \left(\frac{A_i}{A_e}\right) + 1.25545 \times \left(\frac{w_e}{w_i}\right) - 0.48199 \left(\frac{\left(\frac{V}{M}\right)_i}{\left(\frac{V}{M}\right)_e}\right) \tag{28}$$

where $R^2 = 0.8205$. Finally, the constructed yield model is $Y_i = e^{-0.1031408\sigma_i}$.

Table 2. The comparison results of the reference product

	IC-A-P	IC-A-N	IC-B-P	IC-B-N	IC-C-P	IC-C-N
R^2	0.8328	0.8339*	0.8168	0.8182	0.8205	0.8236

*P denotes a positive correlation and N denotes a negative correlation

Secondly, we assume IC-C has a negative correlation (it will be denoted as IC-C-N) with the degree of defect clustering and yield.

The dependent variable and the independent variable are the same as for IC-A and IC-B. The number of data points is 24, as the data of IC-C are not included to perform model fitting. The fitted linear regression model is given by:

$$\hat{\sigma}_i = -0.8648 - 0.04418 \times \left(\frac{N_i}{N_e}\right) + 0.45383 \times \left(\frac{A_i}{A_e}\right) + 1.271 \times \left(\frac{w_e}{w_i}\right) + 0.920435 \left(\frac{\left(\frac{V}{M}\right)_e}{\left(\frac{V}{M}\right)_i}\right) \tag{29}$$

where $R^2 = 0.82364$. Finally, the constructed yield model is $Y_i = e^{-0.1601688\sigma_i}$.

Step 4: Next, we will choose the appropriate reference product. From the results listed in Table 2, the R^2 of IC-A-N is the largest. Hence, the model of IC-A will be chosen as the appropriate reference product in this case. And the regression model of IC-A-N will be taken to estimate the overall scaling factor ($\hat{\sigma}_i$).

Step 5: According to the chosen reference product in Step 4, we can compute the performance evaluation index (PEI) for the two chosen IC products. For IC-1, $\sigma_i = 2.3542$, the PEI is 1.0572 (> 1), and the estimated yield is 0.6633 (the actual yield is about 0.7). For IC-2, $\sigma_i = 2.0571$, the PEI is 0.7649 (< 1), and the estimated yield is 0.6986 (the actual yield is about 0.65). From such a result, we can draw the conclusion that the manufacturing performance of the IC-1 product is better than the IC-2 product. Although IC-1 can be recognized as a maturity product, the performance can still be enhanced (the PEI of IC-1 is very close to 1). The average degree of defect clustering for IC-1 (V/M=5.325) significantly exceeds the critical value ($t_{(0.05,\infty)} \fallingdotseq 1.645$). Hence, the analysis for defect clustering will be necessary corrected action to improve the process performance. Because the PEI value (0.7649) of IC-2 is less than 1, we can recognize that IC-2 is not a maturity product and the manufacturing process should be continuously improved. An improvement regarding defect clustering can be performed, and the related process control may be checked in detail to enhance its process performance.

5 Concluding remarks

In this study, we proposed a simple performance evaluation index to assess the manufacturing performance in the IC manufacturing industry. This evaluation index is constructed according to the modified Poisson yield model, and the related parameters regarding process and product are taken into consideration. In addition, an integrated evaluation procedure is also suggested for the performance evaluation of manufacturing multiple IC products. According to the result obtained from the experimental example, the index and the procedure we proposed will overcome the drawback of using yield and defect count separately in the analysis. Finally, the feasibility of our approach is verified by an illustrative example.

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