Available online at www.sciencedirect.com
ScienceDirect
Expert Systems with Applications 32 (2007) 765–776
Expert Systems with Applications
www.elsevier.com/locate/eswa

The application of control chart for defects and defect clustering in IC manufacturing based on fuzzy theory

Kun-Lin Hsieh [a,*], Lee-Ing Tong [b], Min-Chia Wang [b]

[a] Department of Information Management, National Taitung University, 684, Chung Hua Road, Sec. 1, Taitung 950, Taiwan, ROC
[b] Department of Industrial Engineering and Management, National Chaio Tung University, HsinChu, Taiwan, ROC

Abstract

c-Chart was frequently used to monitor wafer defects during IC manufacturing. The clustering degree of defect on a wafer will increase along with the area of wafer gradually enlarging. The defect clustering causes the Poisson-based c-chart to exhibit many false alarms. Although several revised control charts have been developed to reduce the number of false alarms, those control charts still have some disadvantages in practical use. This study proposes a control chart that applies fuzzy theory and engineering experience to monitor wafer defects with the consideration of defect clustering. The proposed control chart is simpler and more rational than those revised c-charts. Finally, a case study of an IC company, owing to the HsinChu Scientific part at Taiwan, is used to demonstrate and verify the rationality and effectiveness.
© 2006 Elsevier Ltd. All rights reserved.

Keywords: Integrated circuits (IC); Control chart; Defect clustering; Fuzzy theory

1. Introduction

The yield has the directly effect on the manufacturing cost. Hence, it is frequently regarded as an index to evaluate the IC manufacturing performance. Basically, the IC manufacturers with the higher yield will represent the higher competitive power and the better quality. Hence, how to efficiently manage IC process and rapidly enhance their IC yield will become an important study issue. Generally, the yield of IC products can be represented as following formula (Albin & Friedman, 1991):

$$Y_{\text{overall}} = Y_{\text{line}} \times Y_{\text{die}} \times Y_{\text{assembly}} \times Y_{\text{final_test}} \times Y_{\text{quality}} \quad (1)$$

where Y_{overall} is the overall yield of 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; Y_{quality} is the quality yield. Among those yields, the die yield (Y_{die}) is more difficulty to determine than others as for it having a direct effect on productivity than others. Therefore, Y_{die} can be regarded as a primary factor for having direct effect on manufacturing cost. Reviewing the related researches, Y_{die} is frequently mentioned. In this study, the Y_{die} is also the yield we mentioned. Generally, the yield will be affected by the defect (or failure) on a wafer in IC manufacturing. There are many studies to address the defect analysis. However, in this study, the type of defect is not the major consideration. The related content about the theory of defect will be explained well in Jun, Hong, Kim, Park, and Park (1999). The defect count or defect density can be viewed as another index to evaluate the manufacturing performance. However, the state of the defect clustering is gradually occurred along with wafer area increasing. The yield analysis is more complicated since considering the relationship between the defect clustering and yield.

The c-chart was frequently used to on-line monitor the defect count on a wafer for most IC manufacturing. However, the assumption of randomness for defect's location on a wafer and the independent relationship for different defects will be made when the traditional c-chart is used

* Corresponding author. Tel.: +886 89 318855x2656; fax: +886 89 321981.
E-mail address: klhsieh2644@mail200.com.tw (K.-L. Hsieh).

0957-4174/$ - see front matter © 2006 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2006.01.050

to monitor the defect count. That is, the defect count is assumed to obey the Poisson distribution. The clustering status of defects on a wafer had led the assumption to be break. Therefore, if we still use the traditional c-chart to monitor defect count on a wafer, the false alarm (that is, the Type I error) will increase. And, it will let the engineers to ignore the useful information by screening out the control chart. To address such issue, Albin and Friedman (1991) provided a revised c-chart based on the Neyman Type-A distribution to correct the error derived from the conventional c-chart. The concept of designing the revised c-chart is to widen the control limit. Although it can decrease the false alarms comparing with the conventional c-chart, only the variation of defect count between different wafers can be detected. The variation of defect count within a wafer cannot be detected by using it.

Zang (1995) suggested to employ the control chart derived by Albin and Friedman to monitor the defect count on a wafer and construct another control chart based on the clustering index to monitor the defect cluster. The primary concept is to apply the quadratic method and distance method to evaluate the degree of defect clustering. However, the clustering index is difficult to choose and two control charts must be constructed and detected simultaneously. And, it will restrict the applications for Zang's method. Wu (2000) employed Hotelling T^2 control chart to monitor the defect count and the degree of defect clustering. Two responses, the first one is the clustering parameter α and the second is the defect count derived from the negative binominal distribution, are used to construct control chart. However, the assumption of two responses obeying the binormal distribution will be the primary limitation. It will lead to a complicated operation for the real application, e.g., the data transformation.

After reviewing the related literatures, we intend to construct a simple and reasonable control chart to monitor the defect count with the consideration of defect clustering at the same time. Besides, the primary concept been employed is the logical inference during the fuzzy theory. Two phases are designed in our proposed approach: Firstly, the defect clustering degree and defect count will be fuzzied and an inferential value can be obtained. Then, we can use the fuzzy inferential value to construct a control chart to monitor the defect count with the consideration of defect clustering at the same time. Next, we must make the necessary assumptions and conditions for this study:

1. Each defect will have the effect on IC yield. Hence, the larger defect count will denote the worst IC process (the lower yield).
2. No matter the size or the shape of defect, it is regarded as a defect point on a wafer.
3. Defect count and defect clustering degree are reviewed as two responses to control.
4. When the defect count is large and the defect clustering is not significant, the process will be defined as non-normal process.
5. The process denotes unstable when the defect clustering degree is significantly large without taking the defect count into consideration.

This article is organized as five sections: Section 1 will give the motivation and purpose for this study. The related literatures about the control chart used in IC industry and the revised chart are surveyed in Section 2. The proposed procedure is given as Section 3. An illustrative example owing to an IC manufacturer at HsinChu Scientific Park in Taiwan will be employed to demonstrate the rationality and effectiveness of the proposed procedure. Finally, the concluding remarks and suggestions are given as Section 5.

2. Literature review

2.1. Defect clustering index

Stapper (1973, 1985) and Stapper et al. (1983) indicated that the clustering of defects on a wafer becomes more pronounced as the surface area of the wafer increases. Defect clustering violates the assumption on which the c-chart is based: the defects are not independently or randomly scattered on a wafer. Some indices are then developed to measure the defect clustering. Of these cluster indices, the cluster index (CI) proposed by Jun et al. (1999), is proven to be more effective than any others. Moreover, CI does not require any assumptions to be made about the distribution of defects.

Assuming there are n defects on a wafer, and the coordinates of each defect in a two-dimensional plane are given by (X_i, Y_i) for $i = 1,2,\ldots,n$, rearrange X_i and Y_i in ascending order to obtain $X_{(i)}$ and $Y_{(i)}$, where $X_{(i)}$ represents the x coordinate of the ith defect, and $Y_{(i)}$ is the y coordinate of the ith defect. Hence, the intervals V_i and W_i

$$\begin{aligned} V_i &= X_{(i)} - X_{(i-1)}, \quad i = 1,2,\ldots,n \\ W_i &= Y_{(i)} - Y_{(i-1)}, \quad i = 1,2,\ldots,n \end{aligned} \tag{2}$$

where $X_{(0)}$ and $Y_{(0)}$ are set to zero. CI can now be expressed as follows:

$$\begin{aligned} \mathrm{CI} = \min\{&(\text{coefficient of variation of } V_i)^2, \\ &(\text{coefficient of variation of } W_i)^2\} \end{aligned} \tag{3}$$

The mean and variance of V_i can be written as $\overline{V}$ and S_v^2, respectively. The mean and variance of W_i can be written as $\overline{W}$ and S_w^2, respectively. Then, the CI can be expressed as follows:

$$\mathrm{CI} = \min\left\{\frac{S_v^2}{\overline{V}^2}, \frac{S_w^2}{\overline{W}^2}\right\} \tag{4}$$

When the defects are uniformly distributed, the CI index equals one. If CI exceeds one, the defects are clustered. A larger CI corresponds to more severe clustering.

2.2. Poisson c-chart

In IC manufacturing, the number of defects will be one quality characteristic on which the conventional c-chart is typically based. The number of defects used to construct the c-chart must be Poisson-distributed, and so have a probability distribution function given by

$$p(N = n) = \frac{e^{-\mu}\mu^n}{n!} \quad (5)$$

where n represents the number of defects on the surface and μ represents the average number of defects on a wafer. According to the properties of Poisson distribution, the upper control limit (UCL) of the c-chart can be obtained as follows:

$$\text{UCL} = \mu + 3(\mu)^{1/2} \quad (6)$$

Recently, as the surface area of wafers has increased from 4 to 12 in., the clustering degree of wafer defects has becomes more apparent. Hence, using the c-chart to monitor defects will lead to many false alarms.

2.3. Neyman-based c-chart

A modified c-chart based on Neyman Type-A distribution was developed to reduce the number of false alarms. The Neyman Type-A distribution is a member of family for the compound Poisson distributions. Albin and Friedman (1991) proposed a Neyman-based c-chart to improve the traditional c-chart. The Neyman Type-A distribution assumed that the cluster number of defect follows a Poisson distribution with mean λ, and that the number of defects in each cluster is also Poisson-distributed with mean ϕ. The probability distribution function of a Neyman Type-A distribution is as follows:

$$P_n(\lambda, \phi) = P_r(N = n) = \sum_{j=1}^{\infty} e^{-\lambda}\frac{\lambda^j}{j!}e^{-j\phi}\frac{(j\phi)^k}{n!} \quad (7)$$

where n represents the number of defects on a wafer's surface; λ represents the average number of defects on a wafer, and ϕ represents the average number of defects per cluster. The expected value and variance of Neyman Type-A distribution are given as follows:

$$E(x) = \lambda\phi, \quad V(x) = \lambda\phi(1 + \phi) \quad (8)$$

The ratio of $V(x)$ to $E(x)$ is $(1 + \phi)$, so the Neyman-based c-chart widens the control limits on the Poisson-based c-chart. It can therefore effectively reduce the number of false alarms. However, the method proposed by Albin and Friedman still has some shortcomings. They considered the number of defects on a wafer as the quality characteristic, on which to determine the control limits of the Neyman-based c-chart. Their method monitors only the variability of defects among wafers. The variability of the number of defects within a wafer cannot be detected.

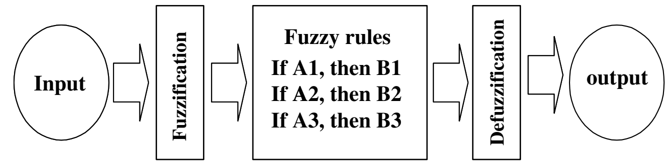

Fig. 1. The process of fuzzy inference.

2.4. Fuzzy theory

Zadeh (1965, 1973) first developed fuzzy theory, which is utilized to deal with fuzzy events. This section will roughly review fuzzy theory. Fuzzy theory is based on fuzzy sets. The characteristic function of a crisp set is defined to be either zero or one, and the relationship of the characteristic function to a fuzzy set is determined with reference to a dichotomy. However, the concept of dichotomy here differs from that typically used. The human language includes many vague words. Therefore, Zadeh used a membership function to represent the intensity: with which one element belongs to one set; a stronger intensity corresponds to a membership function closer to one; a weaker intensity corresponds to a function closer to zero.

A fuzzy proposition has two forms; one is the atomic fuzzy proposition and the other is compound fuzzy proposition. Fuzzy logic is defined as follows:

1. If a compound fuzzy proposition uses "and" to combine two atomic fuzzy propositions, such as 'X is A' and 'y is B', then the membership function can be defined as $\mu_R(x,y) = \min(\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(y)),\ (x,y) \in X \times Y$.
2. If a compound fuzzy proposition uses "or" to combine two atomic fuzzy propositions, such as 'X is A' or 'y is B', then the membership function is $\mu_R(x,y) = \max(\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(y)),\ (x,y) \in X \times Y$.
3. If a compound fuzzy proposition uses "implies" to combine two atomic fuzzy propositions, such as 'X is A' implies 'y is B', then the membership function is $\mu_R(x) = \min(1, 1 - \mu_{\tilde{A}}(x) + \mu_{\tilde{B}}(y)),\ (x,y) \in X \times Y$.

Fuzzy inference is similar to inference in binary logic. The difference between these two inferences is that a fuzzy inference involves contiguous sets, unlike in binary logics, wherein sets are defined absolutely and as opposing each other. A fuzzy inference includes fuzzy steps; many fuzzy steps are combined in a computable system. Some value is imagined to be input into this system. Fig. 1 depicts the process of fuzzy inference. Fuzzy inference provides a different method of control to compare with the traditional method. A fuzzy inference system includes experts' knowledge, operators' experience, the membership function and the development of rules; therefore, the fuzzy inference system is essentially intelligent.

3. The proposed control chart based on fuzzy theory

To achieve process control is our primary goal in this study, two factors significantly affect the performance of

process control: the first one is defect count and the second is the clustering degree of defects. However, there is no suitable rule to define the process's status when simultaneously taking these two factors into consideration. Therefore, we will intend to incorporate the cluster index (CI), defect count on a wafer and the fuzzy theory to construct a control chart to monitor them at the same time. Several steps are developed in the proposed procedure as follows:

Step 1. Get the wafer map of defect

We can capture the wafer map via the particular machine inspection (e.g., KLA machine). Then, the related information about the defect count and the defect distribution on a wafer can be obtained (see Fig. 2).

Step 2. Compute the defect clustering index (CI) for each wafer

After the related information being got after the Step 1, we can compute the clustering index (CI) proposed by Hsieh (2001).

Step 3. Construct the membership function of defect count, clustering index and fuzzy inference value

❑ KLA Defect Data

HH EP031				03-APR-94/11:57:02		CR0334	UP		
WW	6	@06		150	12687474	14713318	-46959		-14658136
DD	1	-5	-1	464558	1361629	1842	2456	0	
DD	2	-5	2	931950	11513248	614	614	0	
DD	3	-4	2	1968340	7677539	4913	3685	0	
DD	4	-4	3	4631605	2216553	7370	6756	0	
DD	5	-3	2	2545674	9836062	6141	4299	0	
DD	6	-3	-3	3883729	2986761	1228	1228	0	
DD	7	-2	-2	5687849	5931209	5527	5527	0	
DD	8	-1	4	2737917	11917774	6756	5527	0	
DD	9	0	2	1566409	3064126	6141	5527	0	
DD	10	1	-3	3970331	5407269	6141	5527	0	
DD	11	1	-3	6138206	10000687	8598	7984	0	
DD	12	2	2	3773793	12826611	4913	4913	0	
DD	13	3	-2	5558416	937994	2456	1228	0	
DD	14	4	-1	3789783	671284	8598	8598	0	
DD	15	4	-1	5216774	9049168	3070	1842	0	

Fig. 2. The wafer map diagram.

As we known, the defect count and the defect clustering are two factors to affect the wafer's yield. Then, we will apply the fuzzy inference to incorporating these two factors. A fuzzy inference value can be obtained. After discussing with the senior engineers, we divide the defect count into seven linguistic description (Hsieh, 2001): very_ low, low, medium_low, medium, medium_high, high, very_high. Next, a triangular function is used to construct the membership function of the above fuzzy sets. Fig. 3 will graphically depict the membership degree of each level.

As for the degree of the defect clustering, after discussing with the senior engineers with their engineering experience, we divide the CI value into 10 levels: from term 1 to term 10 according to the degree of defect clustering. Fig. 4 will represent the membership function of defect CI value.

Due to the defect count and defect clustering index are combined into an inferential value, we will also set the fuzzy inferential value into 10 categories with the consideration of the CI index being divided into 10 categories. They are represented from class 1 to class 10. The corresponding diagram of fuzzy inferential value and their membership value is graphically depicted in Fig. 5.

Step 4. Construct the rule base

The concept being used to construct the control chart is to incorporate the defect count and defect clustering into the final judgment making. According to the rational thinking, we can obtain "if there is many defects on a wafer without the significant defect clustering, it will denote the process as out-of-control; if there is significant defect clustering on a wafer, it will denote the process to be an unstable status". Hence, we can construct the following rules according to the defect count, defect clustering and fuzzy inferential value obtained from the former three steps as follows:

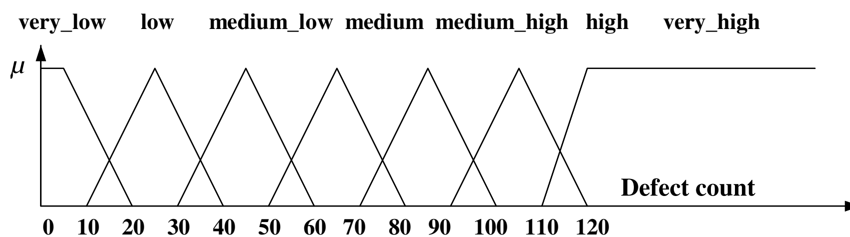

Fig. 3. The membership function of defect count.

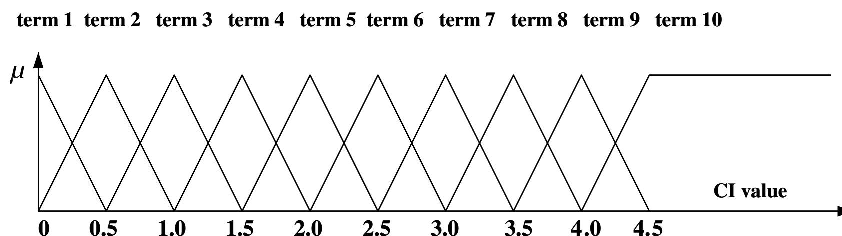

Fig. 4. The membership function of defect CI value.

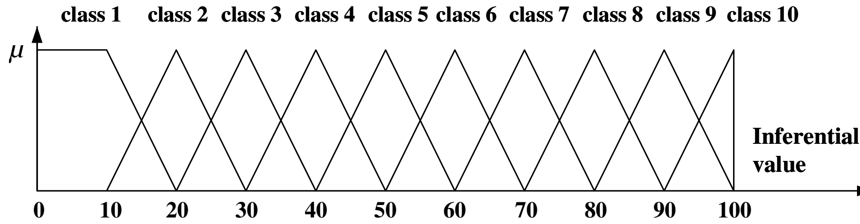

Fig. 5. The corresponding diagram for inferential value and membership value.

R1: IF Defect is very high AND CI is term 1, THEN Value is class 10.
R2: IF Defect is very high AND CI is term 2, THEN Value is class 10.

⋮

Ri: IF Defect is medium AND CI is term 10, THEN Value is class 2.

⋮

R70: IF Defect is very low AND CI is term 10, THEN Value is class 1.

Step 5. Perform the fuzzy inference

In this step, we will input the inspected defect count and the computed CI value into the constructed control chart. Next, the related information about the process will be collected well. For instance, if a wafer had inspected to have 93 defects and CI value was 0.866. When we input (93, 0.866) into the proposed control chart, it will trigger four rules from the rule base:

Rule: IF Defect is medium high AND CI is term 3, THEN Value is class 9.

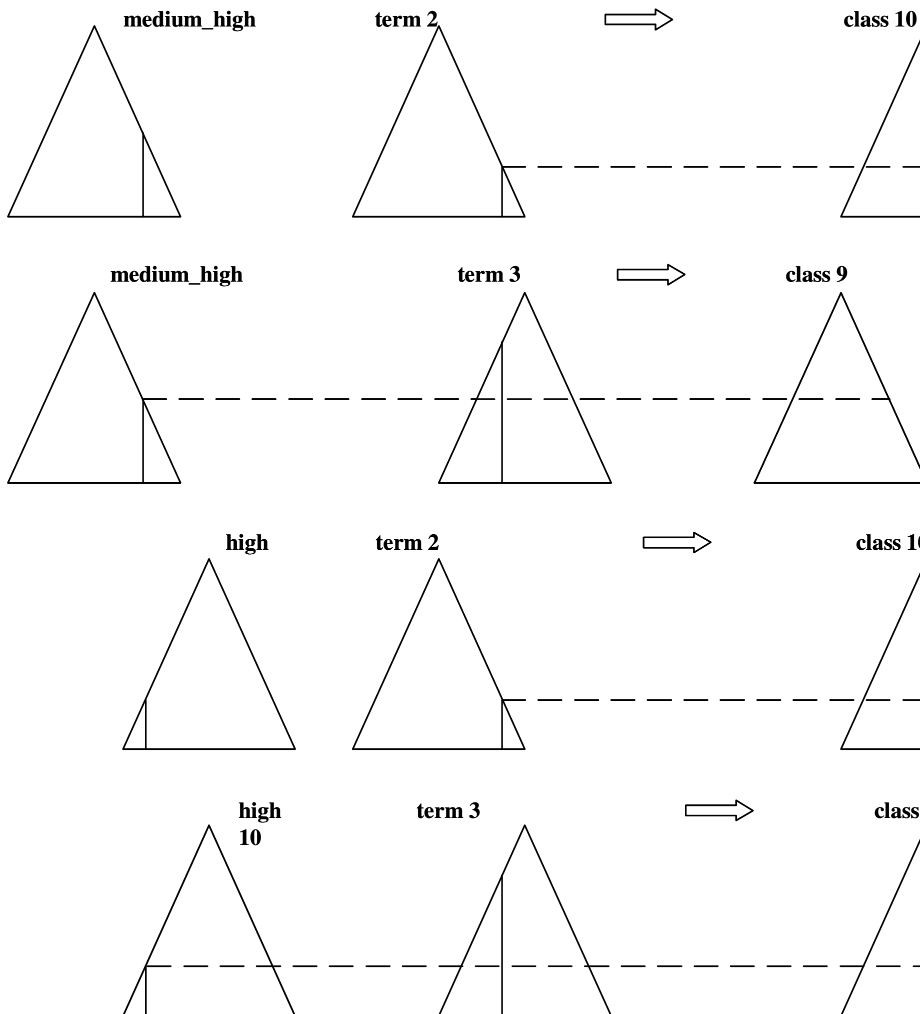

Fig. 6. The inferential process.

Rule: IF Defect is medium high AND CI is term 2, THEN Value is class 10.
Rule: IF Defect is high AND CI is term 2, THEN Value is class 9.
Rule: IF Defect is high AND CI is term 3, THEN Value is class 9.

Next, we will union these fuzzy sets based on the triggered rules to obtain a new fuzzy set (it will denote as the oblique zone). The defuzzification value of new set can be computed as 93.65. The judged making diagram is depicted in Figs. 6 and 7.

Step 6. Compute the control limit and plot the control chart

After the defect data are collected, the defect data are transformed into output of the fuzzy inference rules. Hence, a moving range (X–R_m) control chart can be constructed to monitor simultaneously the number of defects and clustering. If all of the data plotted on the control chart fall within the control limits, then the process is in-control; if there are any points lie outside of the control limits, then the causes must be found and corrected.

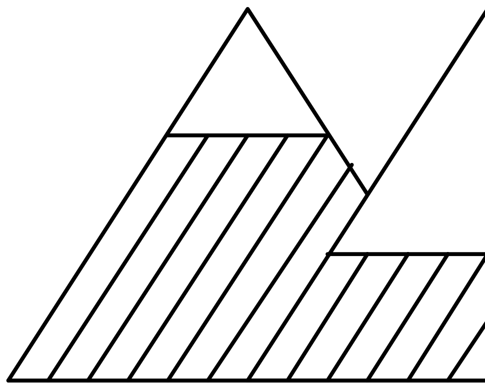

Fig. 7. The union set of fuzzy set.

Step 7. Making the final judgment

The defect count and defect clustering index are incorporated and they must be taken into consideration when making the final judgment. According to the definition of these two attributes, we can obtain the useful information as "Larger defect count and the higher defect CI value will denote the process to be non-normal status." When the process points fall within the control limit, it denotes the process to be in-control. Oppositely, if the process points fall outside the control limit, it denotes the process to be out-of-control. Herein, the judgment criterion will be given as follows: "Process points exceed the upper control limit (UCL) will mean that the defect count is larger and the defect clustering status is not significant; if the process points exceed the lower control limit (LCL), it will mean that the defect clustering is significant and the process is unstable status." For example, process point 1 and point 2 exceed the UCL in Fig. 8, it will denote the two data sets to have the lager defect count. As for process point 3– they exceed the LCL, it will mean that the process is unstable status with the affection of defect clustering.

4. Illustrative example

There are several processes to manufacture 1C including deposition, photolithography exposure, etching, doping and so on. Generally, the engineers will apply equipment to screening out the status of defects on a wafer when the critical process is performed. Then, they will use it to judge the process in-control or out-of-control. In this section, we will employ an IC data set, owing to an IC manufacturer in HsinChu Scientific Park at Taiwan, to demonstrate and

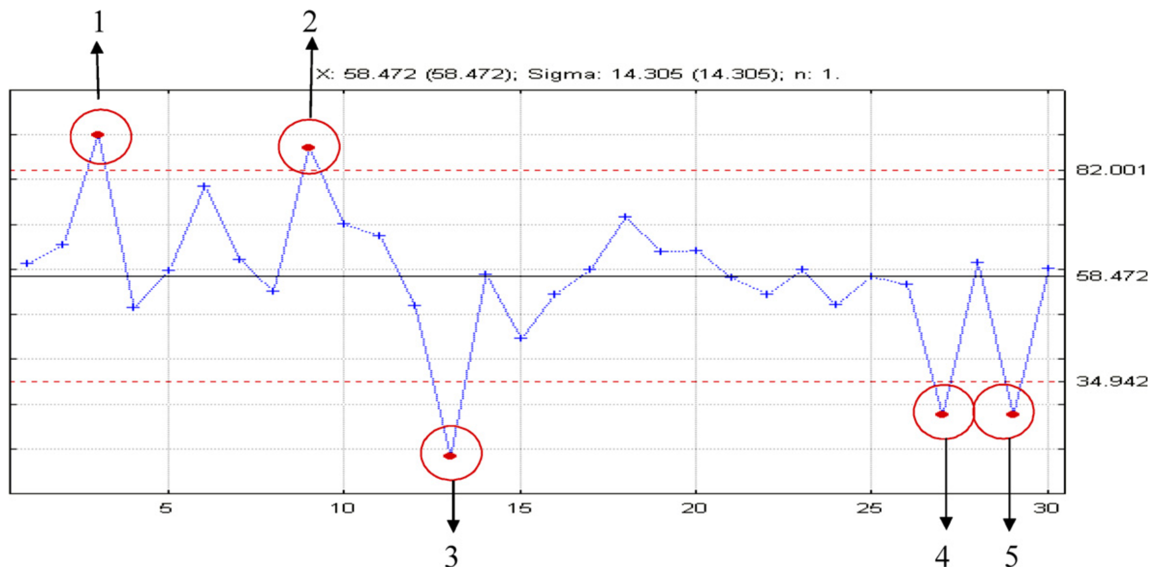

Fig. 8. Example for out-of-control.

verify the proposed procedure step by step. Total of 116 data sets are collected from KLA machine. Herein, we also use the related package (e.g., STATISTICA 6.0 and Fuzzy-TECH) to aid our analysis.

4.1. The result by using the proposed control chart

Step 1. Get the wafer map of defect from KLA 2110 wafer inspection system

KLA 2110 machine can provide the inspection function for wafer's defect. The information including the defect count, the size of defect and the coordinate of defect will be collected by using it. We can capture the wafer map via KLA 2110 inspection system. There are 116 wafer data are collected.

Step 2. Compute the defect clustering for each wafer

We will compute the defect clustering degree of the collected wafer data. As for the defect count of each wafer, it can be got via KLA 2110 inspection system. And, the partial results will be given in Table 1.

Table 1
The defect count and defect clustering index CI for partial data

Wafer number	Defect count	Defect clustering index CI
1	44	3.451
2	37	1.316
⋮	⋮	⋮
109	54	3.069
116	108	6.687

Step 3. Construct the membership function for defect count, defect clustering index CI and fuzzy inference value

The membership functions of defect count, defect clustering index CI and the fuzzy inference values are then constructed by using FuzzyTECH software. It is given in Figs. 9–11.

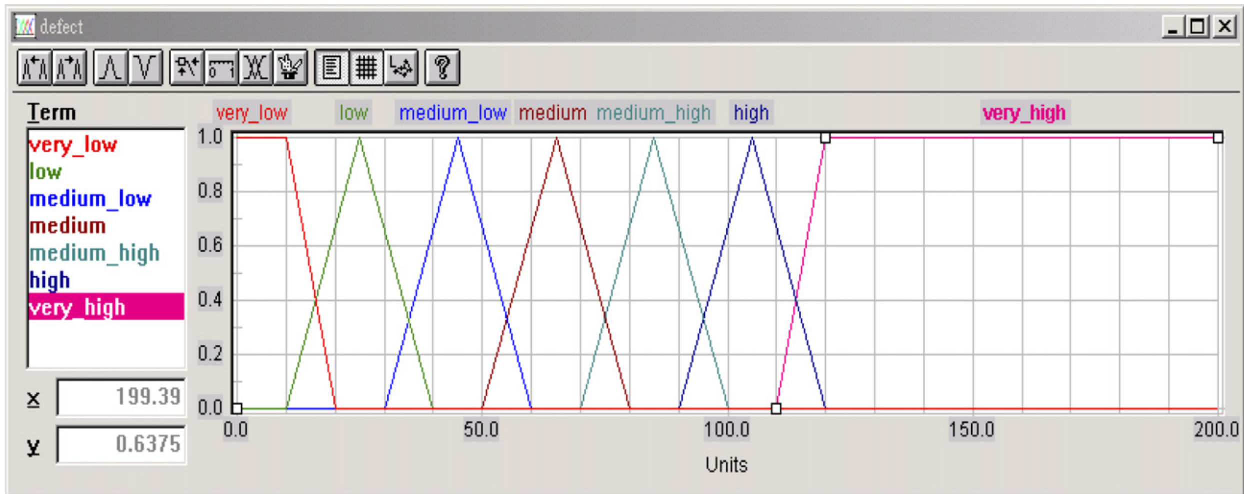

Fig. 9. The membership function of defect count.

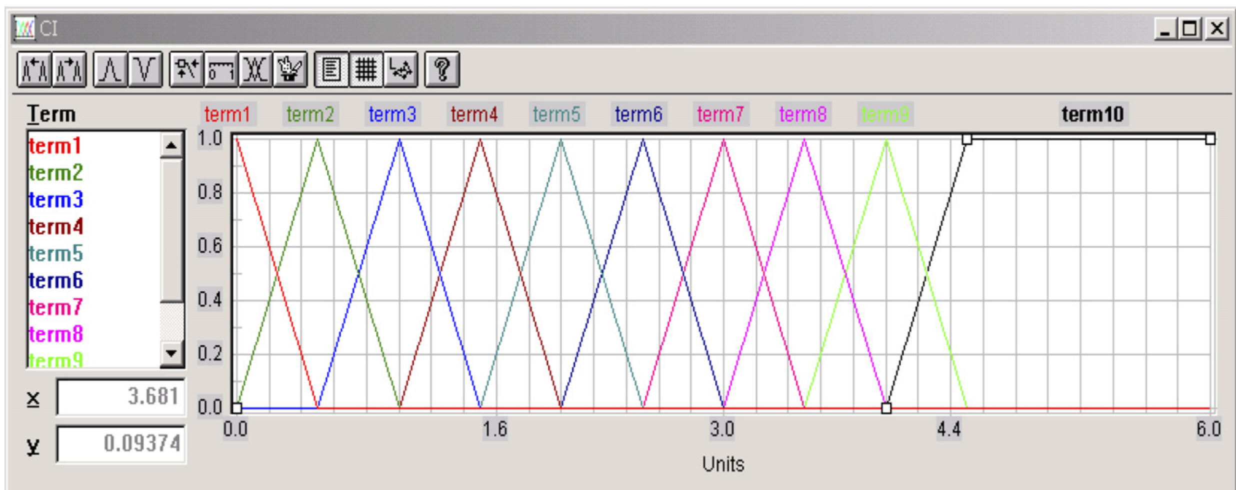

Fig. 10. The membership function of defect clustering index CI.

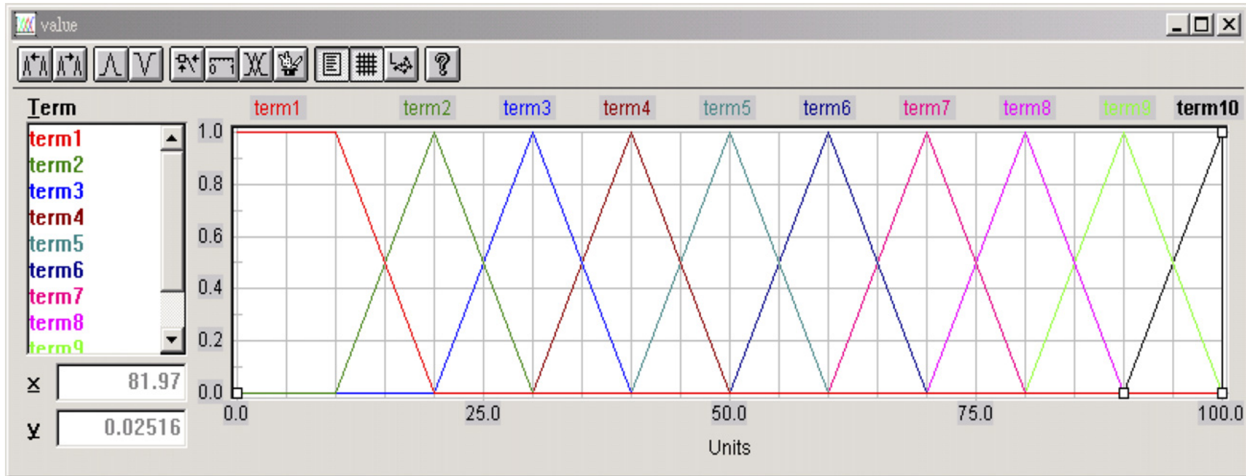

Fig. 11. The membership function of fuzzy inference values.

Step 4. Construct the rule base

The status of Defect count will be divided into seven categories and defect clustering degree will be divided into 10 categories depending on the engineering's experience. That is, there are 70 combinations with the consideration of defect count and defect clustering degree. Then, we will use the package FuzzyTECH to construct the rule base and it is given in Fig. 12.

Step 5. Perform the fuzzy inference

Firstly, a fuzzy control system will be formed by combining the membership function in Step 3 and the rule base in Step 4. Next, we will input the defect count and CI value of each wafer into the fuzzy control system. Finally, a fuzzy inference value of each wafer will be computed and the partial result will be given in Table 2.

Table 2
The fuzzy inference value and the related information for the partial data

Wafer number	Yield (%)	Defect count	CI value	Fuzzy inference value
1	97.980	9	0.434	61.29
2	94.949	21	0.715	65.58
3	70.707	184	2.078	90
4	93.182	30	0.939	51.51
5	93.939	31	1.041	59.75
⋮	⋮	⋮	⋮	⋮
116	94.192	54	3.069	31.6

Spreadsheet Rule Editor - RB1

	IF		THEN	
	defect	CI	DoS	value
7	very_low	term7	1.00	term1
8	very_low	term8	1.00	term1
9	very_low	term9	1.00	term1
10	very_low	term10	1.00	term1
11	low	term1	1.00	term8
12	low	term2	1.00	term7
13	low	term3	1.00	term6
14	low	term4	1.00	term5
15	low	term5	1.00	term4
16	low	term6	1.00	term3
17	low	term7	1.00	term2
18	low	term8	1.00	term1
19	low	term9	1.00	term1
20	low	term10	1.00	term1
21	medium_low	term1	1.00	term9
22	medium_low	term2	1.00	term8
23	medium_low	term3	1.00	term7

Fig. 12. The part of constructed rule base.

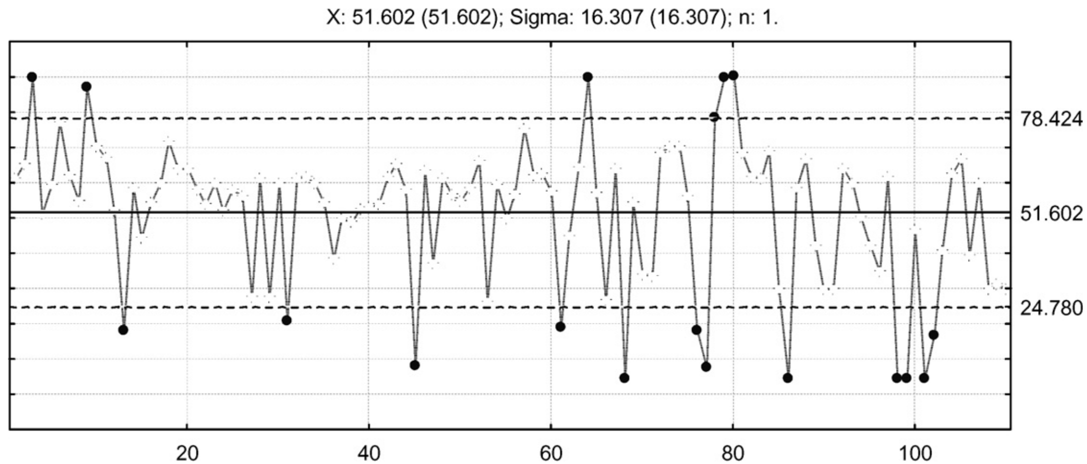

Fig. 13. The constructed control chart.

Step 6. Compute the control limit and plot the control chart

Then, we will use the STATISTICA 6.0 to plot the X–R_m control chart. Herein, the UCL is 78.424 and the LCL is 24.780. After reviewing the control chart, we can find out that six inference values of wafers exceed the UCL and 12 inference value exceed the LCL (marked as • in Fig. 13).

Step 7. Making judgment

After screening out the control chart, we must judge the cause for those out-of-control points. According to the rule of the proposed control chart, the point exceed the UCL will denote the affection from the larger defect count. Comparatively, the point exceed the LCL will denote the affection from the defect clustering. Then, we listed the final judgment for the out-of-control points in Table 3.

From the above result, we can find out that the wafer number of 3, 9, 64, 78, 79 and 80 are detected to out-of-control with the reason of the larger defect count via the proposed procedure (they are listed in Fig. 14). Then, the engineers should recheck the machine to eliminate the non-normal cause. Besides, we can also detect the unstable status with the reason of defect clustering via the proposed procedure (they are listed in Fig. 15). And, from Fig. 14(6), we can find out the latter part of those wafers are significantly out-of-control. That is, the engineers should find out the particular cause by tracing the machine and take the necessary action to prevent it occurring again.

4.2. The comparison with the traditional c-chart

In this section, we will use the same data to plot the traditional c-chart (in Fig. 16). Firstly, the UCL can be computed by software package as 62.8063. Next, we can find out that there are 23 data to exceed UCL. After reviewing the related information, we find out that there are many

Table 3
The cause for each out of control point

Wafer number	Defect count	CI value	Yield (%)	Inference value	Judgment	Cause
3	184	2.077	70.707	90	U	Larger defect count
9	73	0.866	83.586	87.14		
64	135	2.063	80.556	90		
78	72	1.127	84.848	78.63		
79	169	1.976	76.768	90.06		
80	93	1.080	83.081	90.48		
13	79	4.867	94.697	18.45	L	Larger CI value
31	44	3.452	93.939	21		
45	27	3.379	96.717	8.28		
61	28	3.031	97.222	18.92		
68	68	6.422	94.444	4.45		
76	79	5.401	95.202	18.45		
77	47	3.898	95.455	7.94		
86	40	5.253	97.222	4.54		
98	56	7.467	96.717	4.54		
99	39	4.360	96.465	4.54		
101	61	5.81	96.465	4.54		
102	15	2.76	97.727	16.74		

Note: U will denote the point that exceeds the upper control limit, L will denote the point that exceeds the lower control limit.

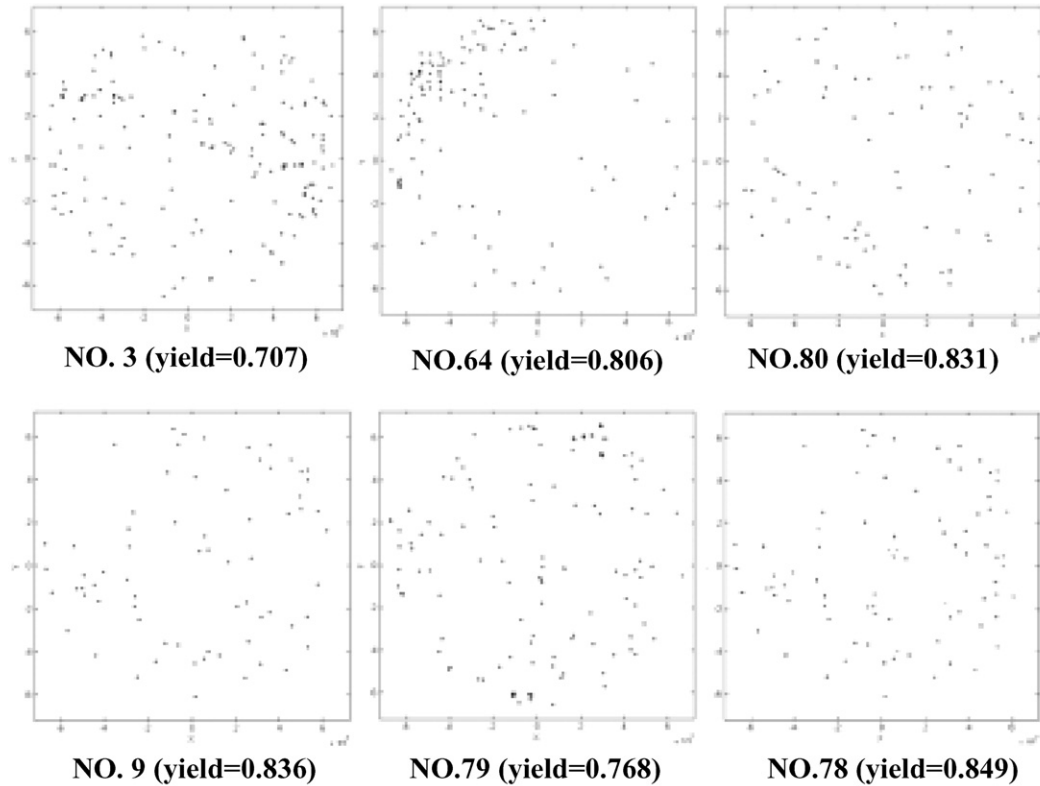

Fig. 14. The wafer map with the number 3, 9, 64, 78, 79 and 80.

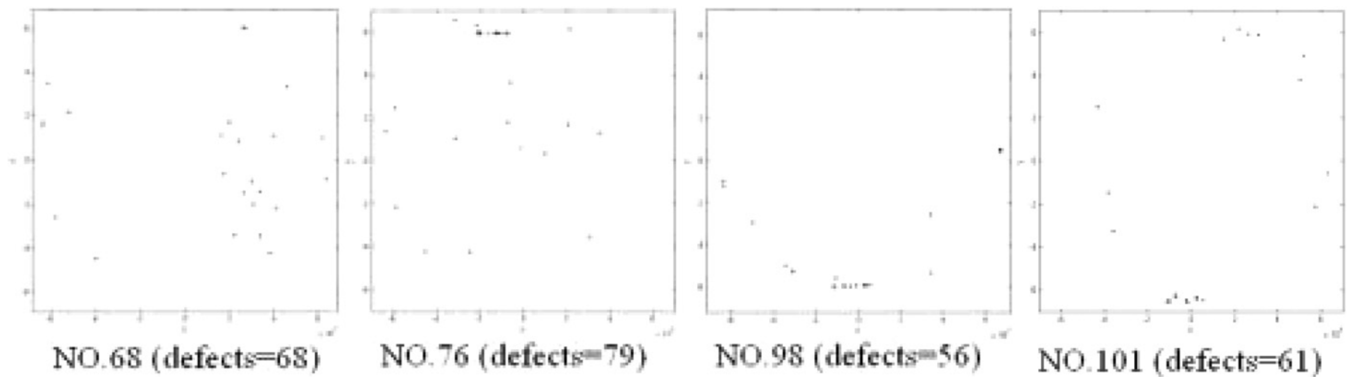

Fig. 15. The wafer map with the number 68, 76, 98 and 101.

false alarms. Those false alarms are occurred due to the defect clustering characteristic. And, the defect clustering characteristic cannot be taken into consideration by using the traditional c-chart.

Comparing with the traditional c-chart, six non-normal wafers can be effectively detected by using the proposed control chart. The rationality and effectiveness of the proposed approach can be verified.

4.3. The comparison with the Albin and Fridman's defect control chart

In this section, we will use the same data to plot the revised defect control chart proposed by Albin and Fridman. Firstly, the average and deviation of the data set will be computed via the following proposed formula:

$$\hat{\phi} = \frac{S^2 - \overline{X}}{\overline{X}}, \quad \hat{\lambda} = \frac{\overline{X}}{\hat{\phi}} = \frac{(\overline{X})^2}{S^2 - \overline{X}} \tag{9}$$

Then, two estimated parameters of Neyman Type-A can be computed as $\hat{\lambda} = 1.49047$, $\hat{\phi} = 30.05461$. Finally, the probability density function of Neyman Type-A can also be derived. If we take three times of standard deviation to be the control limit, we can compute it as about 180 and the control chart can be depicted in Fig. 17.

From Fig. 17, we can find out that the revised defect control chart widens the control limit. Hence, only one data point exceeds the control limit. After reviewing the

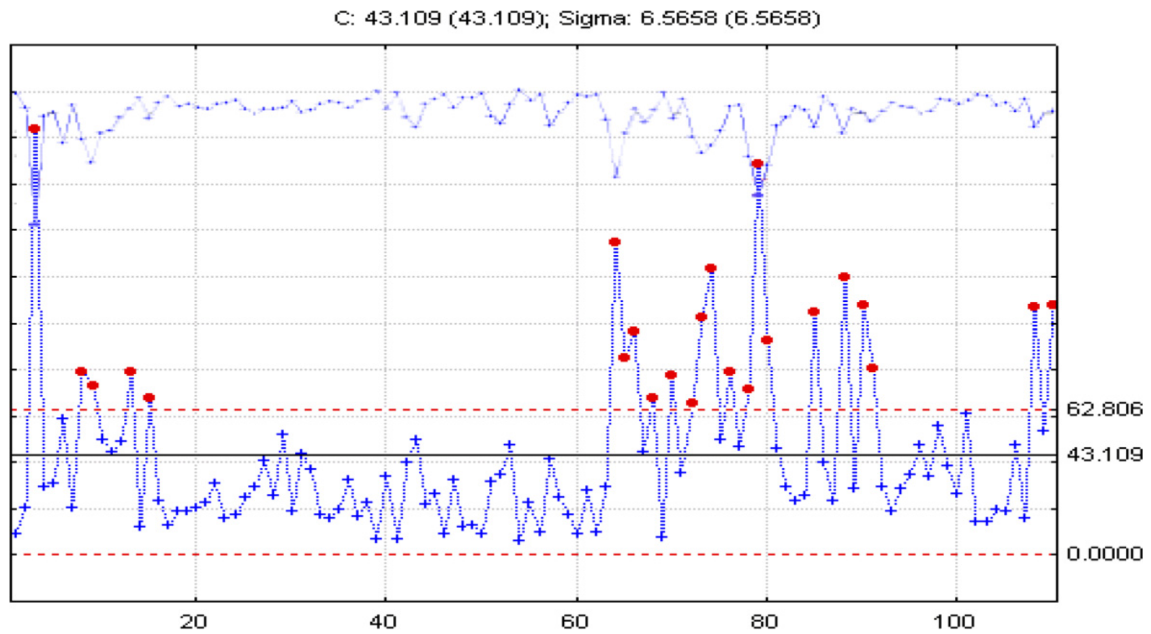

Fig. 16. The traditional c-chart.

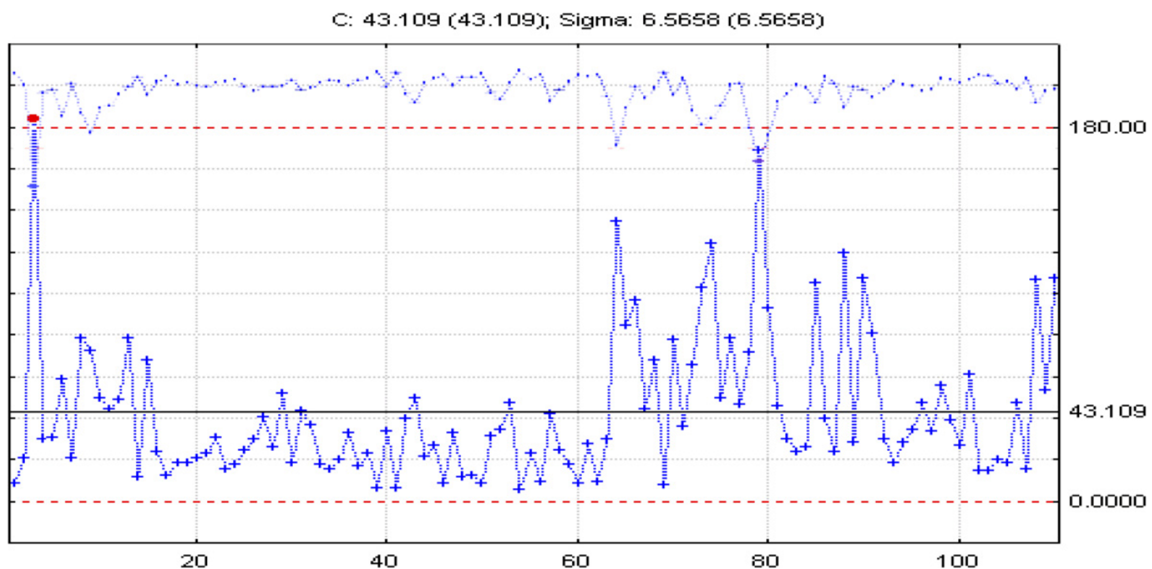

Fig. 17. The revised defect control chart of Albin and Friedman.

yield information, we can find out that the yields of wafer number 3, 9, 64, 78 and 80 are significant low. No any non-normal signals can be detected by the revised defect control chart. Although the false alarms can be reduced by this control chart, the judgment of non-normal status will not be effectively monitored. It also limits the application of the revised defect control chart.

5. Concluding remarks and suggestions

The defects on a wafer are frequently occurred when the area of wafer is gradually enlarged. Not only the IC yield will be affected, but the false alarms will be also increased by using the traditional control charts. It will lead the true variation not to be efficiently controlled. Albin and Friedman had proposed a revised defect control chart based on the distribution of Neyman Type-A to replace it. Although the control limitation can be widened and the false alarms can be decreased, the defect degree on a wafer still cannot be judged well. Then, researchers had suggested to controlling two quality responses. However, the effectiveness of control chart is still limited after being surveyed in the former section. In this study, we apply the fuzzy theory into constructing a control chart to simultaneously control

two responses: defect count and defect clustering degree. Besides, we will use a real IC data set to verify the rationality and application of our approach. Several concluding remarks can be made in this article:

1. The expertise's knowledge and engineer's experience can be included via the proposed fuzzy system. One control chart can be efficiently monitor defect count and defect clustering degree at the same time. It can reduce the amount of actions.
2. The proposed approach does not need complicated formulas, that is, the engineers can be easily construct the control chart without any statistical training.
3. The judgment of the proposed control chart can be easily determined according to whether the process data fall within the control limit or not. If the point falls outside the UCL, it denotes the possible cause to be too many defects. If the point falls outside the LCL, it will denote the possible cause to be the defect clustering.
4. After reviewing the comparison of results, the proposed control chart can demonstrate the better effectiveness than other methods.
5. It will provide an opportunity to packaging the proposed control chart, and it will aid the manufacturers to achieve the on-line control well.

References

Albin, S. L., & Friedman, D. J. (1991). Clustered defect in IC fabrication: Impact on process control charts. *IEEE Transactions on Semiconductor Manufacturing, 4*(1), 36–42.

Hsieh, K. L. (2001). Process improvement in the presence of qualitative response by combining fuzzy sets and neural networks. *Integrated Manufacturing Systems, 12*(6), 449–462.

Jun, C. H., Hong, Y., Kim, S. Y., Park, K. S., & Park, H. (1999). A simulation-based semiconductor chip yield model incorporating a new defect cluster index. *Microelectronics Reliability, 39*, 451–456.

Stapper, C. H. (1973). Defect density distribution for LSI yield calculations. *IEEE Transactions on Electron Devices, ED-20*, 655–657.

Stapper, C. H. (1985). The effects of wafer to wafer density variations on integrated circuit defect and fault density. *IBM Journal of Research Development, 29*, 87–97.

Stapper, C. H., Armstrong, F. M., & Saji, K. (1983). Integrated circuit yield statistics. *Proceedings of IEEE, 71*, 453–470.

Wu, C. H. (2000). Hotelling T^2 control chart combining defect count and defect clustering in IC manufacturing. Master Dissertation, Department of Information Management, National Chaio Tung University.

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control, 8*, 338–353.

Zadeh, L. A. (1973). Outline of a new approach to the analysis of complex systems and decision process. *IEEE Transaction on System, Man and Cybernetics, SMC-3*, 28–44.

Zang, I. H. (1995). IC process control chart with consideration of defect clustering. Master Dissertation, Department of Information Management, National Chaio Tung University.