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# Data transformation in SPC for semiconductor machinery control: A case of monitoring particles

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# Data transformation in SPC for semiconductor machinery control: A case of monitoring particles

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Yield is an important indicator of productivity in semiconductor manufacturing. In the complex manufacturing process, the particles on wafers inevitably cause defects, which may result in chip failure and thus reduce yield. Semiconductor manufacturers initially use wafer testing to control the machine for the number of particles. This machinery control procedure aims to detect any unusual condition of machines, reduce defects in actual wafer production and thus improve yield. In practice, the distribution of particles does not usually follow a Poisson distribution, which causes an overly high rate of false alarms in applying the *c*-chart. Consequently, the semiconductor machinery cannot be appropriately controlled by the number of particles on machines. This paper primarily combines data transformation with the control chart based on a Neyman type-A distribution to develop a machinery control procedure applicable to semiconductor machinery. The proposed approach monitors the number of particles on the testing wafer of machines. A semiconductor company in Taiwan in the Hsinchu Science Based Industrial Park demonstrated the feasibility of the proposed method through the implementation of several machines. The implementation results indicated that the occurrence of false alarms declined extensively from 20% to 4%.

*Keywords*: Machinery control; Semiconductor manufacturing; Control chart; Particle counts

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## 1. Introduction

The electronics industry has grown rapidly in recent years. The major semiconductor manufacturers worldwide have committed themselves to improving production capability under fierce competition, where the yield of wafers is an important indicator of productivity. Therefore, how to control wafers and increase yield has become quite important. The yield of a wafer is defined as the number of functional dies over the total number of tested dies per wafer. Wafer processing typically consists of metal preparation, oxidation, photolithography, etch, diffusion and deposition.

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The fabrication needs multiple steps through the same process at various stages (Limanond *et al.* 1998). In such a complicated wafer-manufacturing process, the particles on wafers will inevitably cause defects, which may result in chip failure and thus reduce yield. Therefore, the number of particles is a critical determinant of the yield of wafers.

Yield can be increased in two ways: process control and machinery control. Process control is realized by monitoring the defects on wafers. However, this research focuses on machinery control. Semiconductor manufacturers use a testing wafer (also called a dummy wafer) to collect the particles on a machine and control the machine for the number of particles. This preparatory operation is implemented before wafers are actually put into production. The unusual conditions of a machine such as a machine out of adjustment or an unusual operator may decrease wafer yield. This study aims to detect any assignable causes of machines by the number of particles and reduce defects in actual wafer production. When the process is improved, we can have few defects in each sample and thus a high-yield process can be achieved.

The *c*-chart, a statistical process control (SPC) instrument, can be applied to particle control. The Poisson assumption implies that the occurrence of a defect in any location is independent, i.e. defects are uniformly scattered over a sample (Albin and Friedman 1991). In most cases, the distribution of particles, however, does not follow a Poisson distribution, which causes an overly high rate of false alarms. As a result, the operating staff cannot appropriately control the machine for the number of particles.

In recent years, the size of wafers has grown from 2, 4, 6 and 8 to 12″, which makes clustered defects on wafers increasingly noticeable. It has been widely reported that defects generated in an IC fabrication tend to cluster (Stapper *et al.* 1983, Stapper 1985). The continuous use of traditional *c*-chart may send out many incorrect 'out-of-control' signals that are false alarms. Albin and Friedman (1989) adopted the Neyman type-A distribution for monitoring clustered defects in IC fabrication. Albin and Friedman (1991) developed a monitoring procedure based on Neyman distribution to discriminate between data from an in-control process that yields clustered defects and data from an out-of-control process. Su and Tong (1997) applied neural technique (e.g. a fuzzy ART network) and a Neyman-based control chart to monitor the clustered defects in semiconductor manufacturing.

The traditional *c*-chart does not permit any data inconsistent with Poisson distribution. When defects do not follow a Poisson distribution, the traditional process control causes many false alarms. From the literature mentioned above, the application of a Neyman type-A distribution is based on the assumption that clustering exists. Some previous papers (e.g. Albin and Friedman 1991, Su and Tong 1997) have taken clustering phenomena into consideration, but for the study of defects in wafer production not the number of particles on machines. There is a problem for applying a control chart on the final wafer production data. When an assignable cause is detected, it is necessary to make more effort to find out which machine is out of control (i.e. the assignable machine).

This study aims to develop a machinery control procedure to monitor the number of particles on the testing wafer of machines. The proposed approach has no need of recording the coordinates of particle locations. Consequently, the inspection time is excessively reduced. Without the need of much available data, this study combines data transformation with the particle chart based on a Neyman type-A

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distribution. The developed machinery control procedure monitors the number of particles on testing the wafer of a machine so that operators can monitor the conditions of machines promptly.

The developed procedure monitors the number of particles on a testing wafer, which exhibits the same properties of the number of defects on a wafer. The following assumptions are made:

- Particles on a testing wafer can be detected.
- All particles provide the same explanation or indication about the condition and reliability of machines. The larger the number of particles, the worse the machine's condition.
- Every particle on a testing wafer is considered a defect regardless of the size of the particle.

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## 2. Process control methods

SPC tries to detect the occurrence of any abnormality in the process before more defective products are manufactured and make the necessary correction to improve yield and product quality. To control the number of defects, *c*-charts can be developed to control either the total number of defects in a unit or the average number of defects per unit. These two types of *c*-charts assume that when the sample size is fixed, the probability of a defect occurrence in each sample exhibits a Poisson distribution. Consequently, they must satisfy the following assumptions:

- Location of a defect occurrence on the product is randomly distributed, i.e. the probability for the defect falling anywhere on the product is the same.
- Defects are independent of each other, i.e. the occurrence of a defect on the product is irrelevant to any other defects.

### 2.1 *Standard* c-*chart*

When the number of defects of a product exhibits a Poisson distribution, the probability distribution function is:

$$\text{Prob}\,(N = n) = \frac{e^{-c}c^{n}}{n!} \tag{1}$$

where $n$ is the number of defects and $c$ is the parameter of Poisson distribution, which is the average number of defects. Based on the properties of Poisson distribution, the upper and lower limits for defect control can be obtained by the following equations assuming that a standard value for $c$ is available (Montgomery 2000):

$$\text{UCL} = c + 3\sqrt{c}, \tag{2a}$$

$$\text{CL} = c, \tag{2b}$$

$$\text{LCL} = c - 3\sqrt{c} \tag{2c}$$

where $c$ is the average number of defects, UCL, CL and LCL are the upper control, central and lower control limits, respectively. If $\text{LCL} < 0$, then assume $\text{LCL} = 0$.

In addition, if $c$ is unknown, then the average number of defects, $\bar{c}$, in a preliminary sample of inspection units can be used to estimate $c$.

### 2.2 *Particle control chart based on the Neyman distribution*

The attribute data are commonly encountered in the semiconductor manufacturing. Many authors have made an effort to develop a control chart for attribute data. Glushkovsky (1994) developed a *G*-control chart for attribute data. Lu *et al.* (1998) dealt with multivariate attribute processes and developed a multivariate *np* chart (MNP) chart. Shore (2000) recommended a general framework for constructing Shewhart-like control charts for attributes based on fitting a quartile function. Xie *et al.* (2001) considered the excessive number of zero count data and used a zero-inflated Poisson model in statistical process control. Somerville *et al.* (2002) developed a filtering and smoothing method that uses an exponentially weighted moving average (EWMA) and Poisson probabilities for mixed particle count distributions. Related literatures can be found in Hansen and Thyregod (2000) and Tannock (2003). Recently, advanced process control has been used in semiconductor manufacturing (Box and Luceño 1997, Del Castillo 2002, Su and Hsu 2004). This approach applies a run-to-run controller actively to feedback the process disturbance by adjusting the manipulated variables.

The above-mentioned literature did not take the clustering attribute data into consideration. Albin and Friedman (1991) proposed a control procedure based on a Neyman type-A distribution to monitor processes with clustering defects. For detailed discussions of clustering distributions, see Jackson (1972) and Johnson *et al.* (1992). A Neyman type-A distribution is a compound Poisson distribution that assumes that the number of defect clusters exhibits a Poisson distribution and the defects in every cluster adhere to another Poisson distribution. The fundamental assumptions include the following:

- Number of defect clusters follows a Poisson distribution with an expectation of $\lambda$.
- Number of defects in individual clusters follows a Poisson distribution with a mean of $\phi$.

The density function for the Neyman type-A distribution is as follows:

$$\begin{aligned} P_n(\lambda,\phi) &= \Pr(N=n) = \sum_{j=1}^{\infty} e^{-\lambda}\frac{\lambda^j}{j!}e^{-j\phi}\frac{(j\phi)^n}{n!}, \quad n = 1,2,3,\ldots; \\ P_0(\lambda,\phi) &= \Pr(N=0) = e^{-\lambda(1-e^{-\phi})}, \quad n=0. \end{aligned} \tag{3}$$

The mean and variance of a Neyman type-A distribution can be expressed as:

$$E(x) = \lambda\phi, \tag{4a}$$

$$V(x) = \lambda\phi(1+\phi). \tag{4b}$$

Since the ratio between the variance and the mean is $(1+\phi)$, the particle charts derived from a Neyman type-A distribution loose up the control limits of the traditional $c$-charts, which thus effectively reduce the occurrence of false alarms. The parameters $\lambda$ and $\phi$ can be estimated by using the maximum likelihood estimate (MLE) method, which can be found in Johnson *et al.* (1992). In practice, the

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method of moments estimates tends to be used due to their closed form format and easy computation:

$$\hat{\phi} = \frac{S^2 - \bar{X}}{\bar{X}}, \tag{5a}$$

$$\hat{\lambda} = \frac{\bar{X}^2}{S^2 - \bar{X}} \tag{5b}$$

where $\bar{X}$ is the sample mean and $S^2$ is the sample variance. The control limits based on a Neyman type-A distribution can be derived from the following equations:

$$\sum_{n=0}^{\mathrm{UCL}} p\,(N = n) = 1 - 0.0013 \quad \text{and} \quad \sum_{n=0}^{\mathrm{LCL}} p\,(N = n) = 0.0013 \tag{6}$$

where $p\,(N = n)$ is given in equation (3). And when the process is in-control, the probability a sample point is outside the control limits is 0.0027. The related statistical theory of the Neyman distribution (e.g. type I and II errors) can be found in Johnson *et al*. (1992).

When the parameter ($\lambda$) is large and the mean ($\lambda\phi$) does not approach zero, the Neyman distribution approximates to the normal distribution (Johnson *et al*. 1992). Therefore, the control limits can be simply obtained by the following equations:

$$\mathrm{UCL} = \lambda\phi + 3\sqrt{\lambda\phi(1+\phi)}, \tag{7a}$$

$$\mathrm{LCL} = \lambda\phi - 3\sqrt{\lambda\phi(1+\phi)}. \tag{7b}$$

## 3. Proposed machinery control procedure

This study proposes an approach to control the number of particles on machines and thus control any abnormal conditions on machines. To deal with the problem of overly high occurrence of false alarms caused by particle distribution inconsistent with a Poisson distribution on the testing wafer of semiconductor machinery, the developed approach primarily combines a Neyman type-A distribution and the data transformation method. The proposed approach is illustrated in figure 1 and the detailed steps are explained as below.

*Step* 1: Obtain the data of particles by wafer inspection system.

In this study, the number of particles on a testing wafer is used for machinery control. Consequently, the number of particles on the machines' testing wafer is collected.

*Step* 2: Test whether the particle distribution exhibits a Poisson distribution.

Whether the particle distribution exhibits a Poisson distribution is determined by the non-parametric Kolmogorov–Smirnov (K–S) test. If yes, *c*-charts will be used to determine control limits. Otherwise, further outlier analysis as presented in Step 3 will be conducted.

*Step* 3: Conduct outlier analysis.

When the data do not satisfy a Poisson distribution, it may indicate that the machinery is already out of control. To avoid any impact of outliers on *c*-chart construction, outlier analysis can be used to study their causes. F-Spread (Fourth Spread) developed by Hoaglin *et al*. (1986) is adopted

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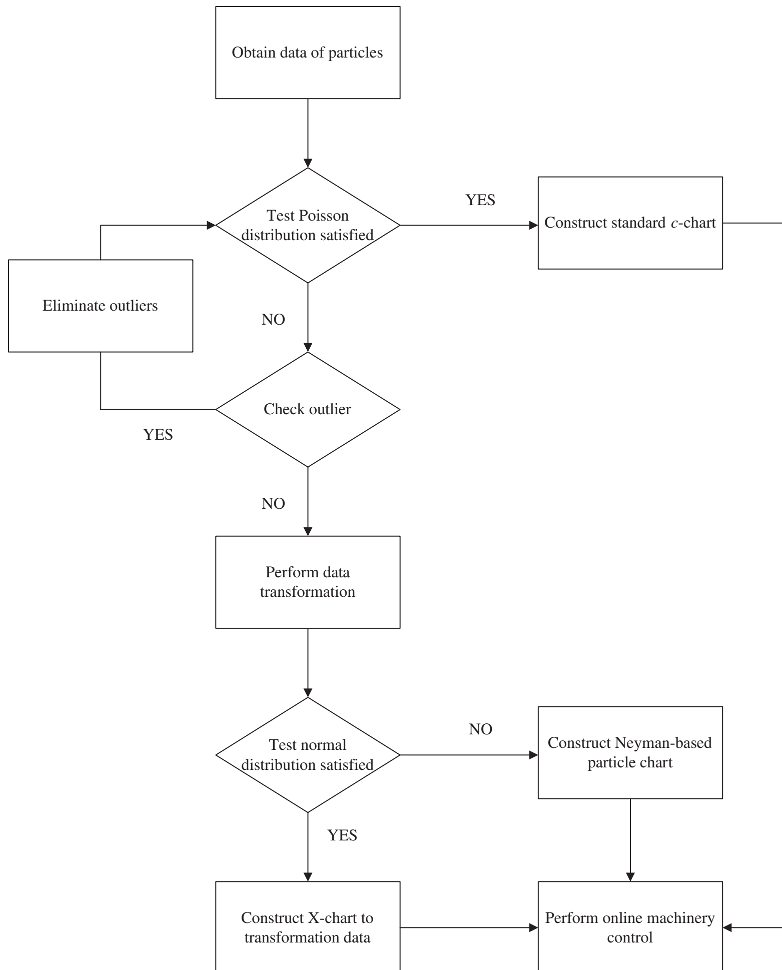


Figure 1. Flow chart of the proposed machinery control approach.

herein to identify outliers. If these causes are assignable, then the corresponding samples will be eliminated. If these causes are not assignable, then these samples will remain. After outliers are eliminated, the procedure returns to Step 2. If the Poisson distribution is satisfied, then *c*-charts will be used to establish control limits. If the Poisson distribution is still not satisfied, then the procedure moves on to Step 4.

*Step* 4: Perform data transformation.

Based on the data obtained from Step 3, the mean and variance of a number of particles are calculated, and the particle data are transformed by square-root transformation (Johnson and Wichern 1988). If the distribution of defects can be converted to a normal distribution, control charts for individual units will be developed by the following steps (Montgomery 2000):

- Calculate the average, $\bar{X} = (\sum_{i=1}^{m} X_i/m)$, where $X_i$ is the *i*-th transformed data point and $m$ is the number of transformed data points.

- Calculate the moving range, $\mathrm{MR}_i = |X_i - X_{i-1}|$, $i > 1$.
- Calculate the moving-average, $\overline{\mathrm{MR}} = (\sum_{i=2}^{m} \mathrm{MR}_i / m - 1)$.
- Establish the X-chart for individual units as below:

$$\mathrm{UCL}_x = \bar{X} + 3\sigma_x = \bar{X} + 2.66\overline{\mathrm{MR}}, \tag{8a}$$

$$\mathrm{CL}_x = \bar{X}, \tag{8b}$$

$$\mathrm{LCL}_x = \bar{X} - 3\sigma_x = \bar{X} - 2.66\overline{\mathrm{MR}}. \tag{8c}$$

If a normal distribution cannot be realized through data transformation, then go to Step 5.

The SPC tools are usually built on the assumption of a normal distribution. The data not normally distributed will be transformed to do so. In general, square-root transformation is most appropriate for attributes data (Johnson and Wichern 1988). The number of particles reflects an aspect of attributes; therefore, square-root transformation can convert particle data to a normal distribution. Levinson and Polny (1999) and Levinson *et al.* (2001) found the similarity between a Gamma distribution and a Poisson distribution when the average number of particles is fairly large. Hence, the number of particles that do not exhibit a Poisson distribution may satisfy a Gamma distribution (Levinson and Polny 1999):

$$f(x) = \frac{r^{\alpha}}{\Gamma(\alpha)} x^{\alpha-1} e^{-rx} \tag{9}$$

where $\alpha$ is the shape parameter and $\beta$ is the scale parameter. Let $y = 2rx$, then

$$g(y) = \frac{1}{2^{\alpha}\Gamma(\alpha)} y^{\alpha-1} e^{-2/y}. \tag{10}$$

Since $v = 2\alpha$, $g(y) = \left(1/2^{v/2}\Gamma(v/2)\right) y^{(v/2)-1} e^{-y/2}$ is the Chi-square distribution with degrees of freedom $v$. Subsequently, $\sqrt{2rx}$ should follow approximately a normal distribution (Johnson and Kotz 1970) with mean $(\sqrt{2}/2)\sqrt{2v-1}$ and variance of 0.5. Therefore, the Chi-square distribution can be converted to a normal distribution by a square-root transformation. Finally, the individual control chart based on a normal distribution can be applied.

*Step* 5: Build Neyman-based particle control charts.

If the data do not satisfy a Poisson distribution and cannot be converted to a normal distribution through square-root transformation, it indicates that particles may not be independent of each other or clustering exists. In such cases, the particle control charts built on a Neyman type-A distribution can be applied. In this study, the sensitizing rule is one or more points outside of the control limits.

*Step* 6: Perform online machinery control.

If all the observations occur randomly within certain control limits, then the control limits will be defined as the limits of the control chart. If there are one or two outliers, the causes should be researched and overcome. Control limits will be re-computed after the outliers are eliminated.

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## 4. Case study

### 4.1 *Case description*

The feasibility of the proposed machinery control method was demonstrated through the actual data provided by a semiconductor company of Taiwan in Hsinchu Science Based Industrial Park. In the past, the semiconductor company applied standard $c$-charts to particle control. However, the operators could not correctly determine the condition of machines by $c$-charts due to excessive false alarms. This situation may result from the particle distribution not being consistent with Poisson distribution.

The company usually takes steps to test machines before production. To protect the confidentiality of data, the Quality Manager specifies randomly to a sample of nine machines from more than 200 machines on the shop floor. The nine machines under study are mainly placed at the phase of wafer manufacturing. Table 1 describes the process and location of machines.

When particle distribution on machines does not exhibit a Poisson distribution, the use of $c$-charts to control the number of particles will result in an overly high occurrence of false alarms. Figure 2 shows the $c$-chart for machine K1, where 33 of 100 raw data points for particle counts fall out of control limits. However, the actual number of out-of-controls is not as many as shown. Therefore, when particle distribution does not exhibit a Poisson distribution, the resulting $c$-chart shows an overly high occurrence rate of false alarms. The following section is intended to explain how the control procedure proposed in this study can solve this problem and realize the goal of semiconductor machinery control.

### 4.2 *Implementation results*

The nine machines mentioned above are used in this case study. We demonstrate the control procedure developed in Section 3 and solve the problems associated with the case when collected data do not fit the assumption of Poisson distribution. The implementation is illustrated as follows:

*Step* 1: Obtain the data of particles by wafer inspection system.

Operators collected data concerning the number of particles on a testing wafer by using inspection equipment. The data were collected during the last four months in 2002.

Table 1. Description of machines.

| Machine | Area | Description |
|---|---|---|
| K1 | Diffusion | Diffusion furnace SiN deposition |
| K2 | Diffusion | Diffusion furnace SiN deposition |
| A1 | Photolithography | Photoresist/exposure/developer (Scanner) |
| A2 | Photolithography | Photoresist/exposure/developer (Stepper) |
| P1 | Etch | Polyetcher (Chamber C) |
| M1 | Diffusion | Diffusion implanter |
| C1 | Thin film | Film TEOS/TEOSPGS polish (Chamber A) |
| C2 | Thin film | Film TEOS/TEOSPGS polish (Chamber B) |
| S1 | Thin film | Film TESO/TEOSPSG deposition |

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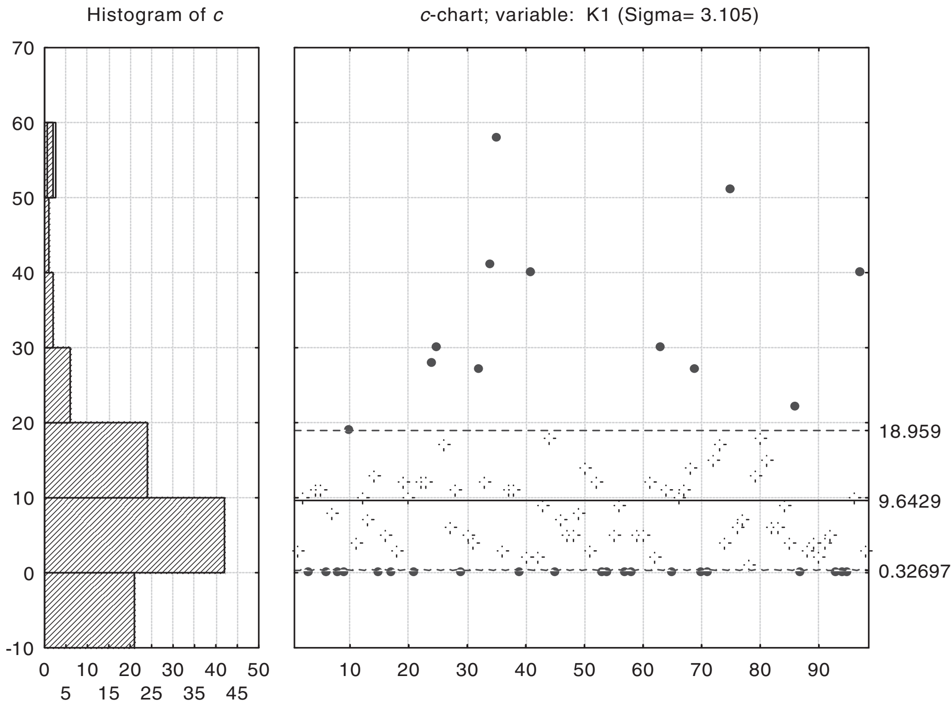


Figure 2. Standard $c$-chart of machine K1.

*Step* 2: Test whether particle distribution exhibits a Poisson distribution.

The non-parametric K–S test is employed to determine if particle distribution satisfies a Poisson distribution. If yes, $c$-charts can be immediately constructed to control the number of particles on machines. In the nine machines under study, A1, A2 and S1 are qualified for a Poisson distribution. The $c$-charts based on a Poisson distribution are thus developed to control the number of particles on these machines. Figure 3 shows machine A1's $c$-chart as an example. The $c$-chart is used to control the number of particles on machine A1. Similar $c$-charts can also be developed for machines A2 and S1. The other six machines that do not qualify for a Poisson distribution will move on to the next step.

*Step* 3: Conduct outlier analysis.

If the data distribution that is inconsistent with a Poisson distribution is attributable to an out-of-control process, this status can be fixed by identifying the outliers through outlier analysis and finding the causes. If these causes are assignable (e.g. operational negligence), the corresponding samples will be eliminated. If not assignable, the samples will remain. After outliers are taken out, return to Step 2. If a Poisson distribution is satisfied, $c$-charts will be constructed to determine control limits. Otherwise, go to the next step. For the outliers detected by the outlier analysis, we discussed the elimination criterion with the manufacturing engineers. The detected outliers were eliminated from the sample set provided that their numbers of particles exceed twice as many of

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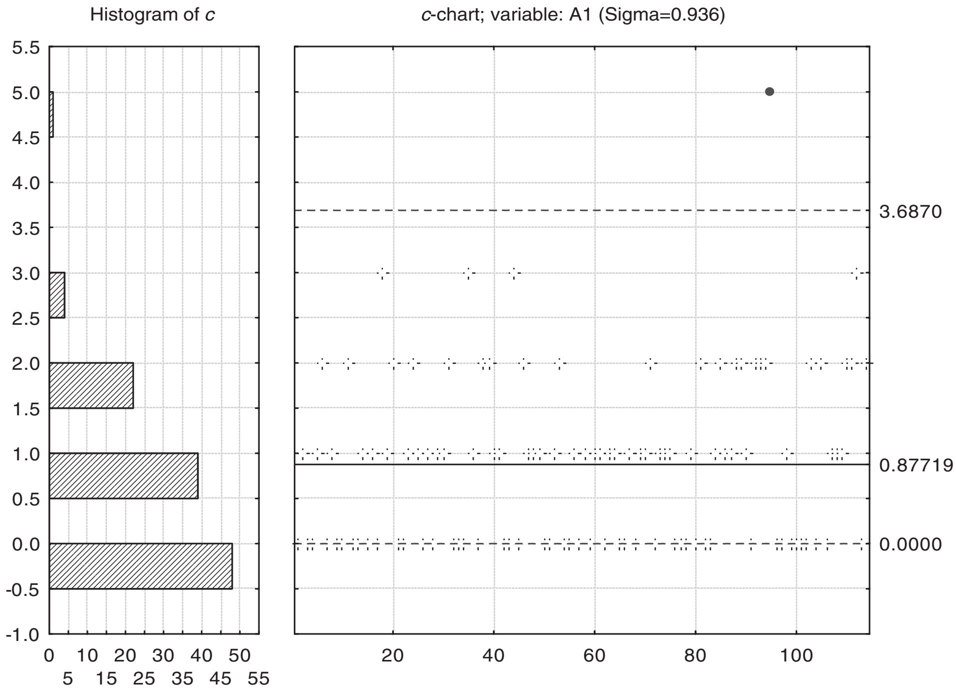


Figure 3. Standard $c$-chart of machine A1.

specification. After outliers are eliminated, the K–S test is performed again to determine if a Poisson distribution is satisfied. However, six machines such as K1, K2, P1, M1, C1 and C2 still do not exhibit a Poisson distribution. Hence, Step 4 is pursued.

*Step* 4: Perform data transformation.

Square-root transformation is conducted on the number of particles after outliers are eliminated. Then the transformed particle data are tested for the existence of a normal distribution by K–S tests. If a normal distribution is satisfied, control charts for individual units based on a normal distribution are constructed. If not, go to Step 5. Among the six machines under study, three show a normal distribution after data transformation: K1, K2 and P1. Figure 4 shows machine P1's normal distribution plot after data transformation.

In figure 4, the transformed particle data and probabilities show a linear relationship, which reflects normal distribution. The level of confidence interval used in this study is 95%. The resulting $p$-value from the K–S test $>0.1$, indicating that the hypothesis of a normal distribution cannot be rejected. Next, the X-charts for individual units are constructed based on transformed data. Figure 5 (a) shows machine P1's X-chart, which can be used to control machine P1's number of particles. By comparing machine P1's post-transformation individual control chart to the standard $c$-chart (figure 5 (b)), the control procedure proposed in this paper has substantially reduced false alarms. Similarly, the false alarms on machines K1 and K2 have also been significantly decreased.

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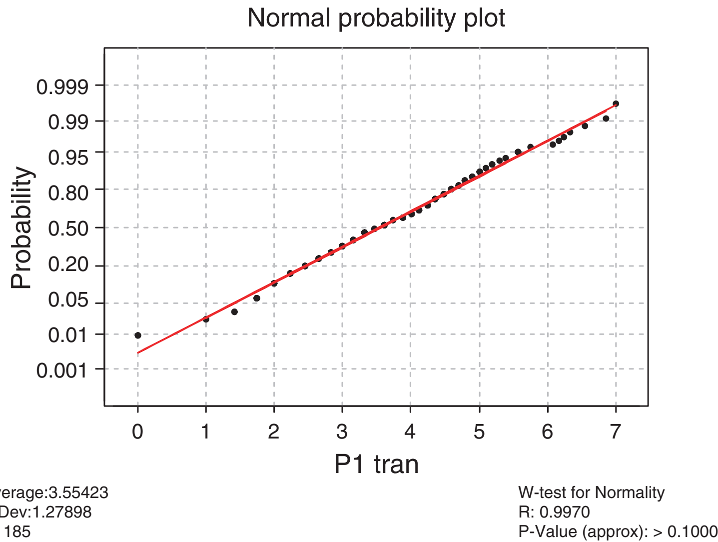


Figure 4. Normal probability plot of machine P1—after data transformation.

*Step* 5: Build Neyman-based particle control charts.

The remaining three machines that cannot be converted to a normal distribution are M1, C1, and C2. We use the original particle data to build the particle control charts based on a Neyman type-A distribution. First, the parameters of a Neyman type-A distribution are computed by equations (5a) and (5b). Take machine C1, for example; the average number of particles is $\bar{X} = 5.52$, sample variance is $S^2 = (5.61)^2$. Hence, the estimated parameters of a Neyman type-A distribution are:

$$\hat{\lambda} = \frac{(5.52)^2}{(5.61)^2 - 5.52} = 1.174; \quad \hat{\phi} = \frac{(5.61)^2 - 5.52}{5.52} = 4.7.$$

Taking the above-estimated parameters into equations (7a) and (b), the corresponding upper and lower limits are computed as: $\text{UCL} = 5.52 + 16.83 = 22.35$; $\text{LCL} = 0$. Figure 6 (a) shows machine C1's Neyman-based particle control chart. Compared with the standard *c*-chart as shown in figure 6 (b), the Neyman-based particle control chart demonstrates better control effects.

*Step* 6: Perform online machinery control.

The final step is to control the number of particles on machines using the control charts developed from the previous steps. When particles fall out of the control limits (i.e. the number of particles is out of control), the machine is assumed to be under abnormal conditions such as machine deterioration and an unskilled operator. The manufacturing engineers must understand the situation and confirm whether the machine is truly functioning abnormally. If it is, the cause must be identified so that the machine can be adjusted appropriately.

From our implementation results, the Neyman-based control limits are wider than the Poisson-based control limits. Therefore, the proposed

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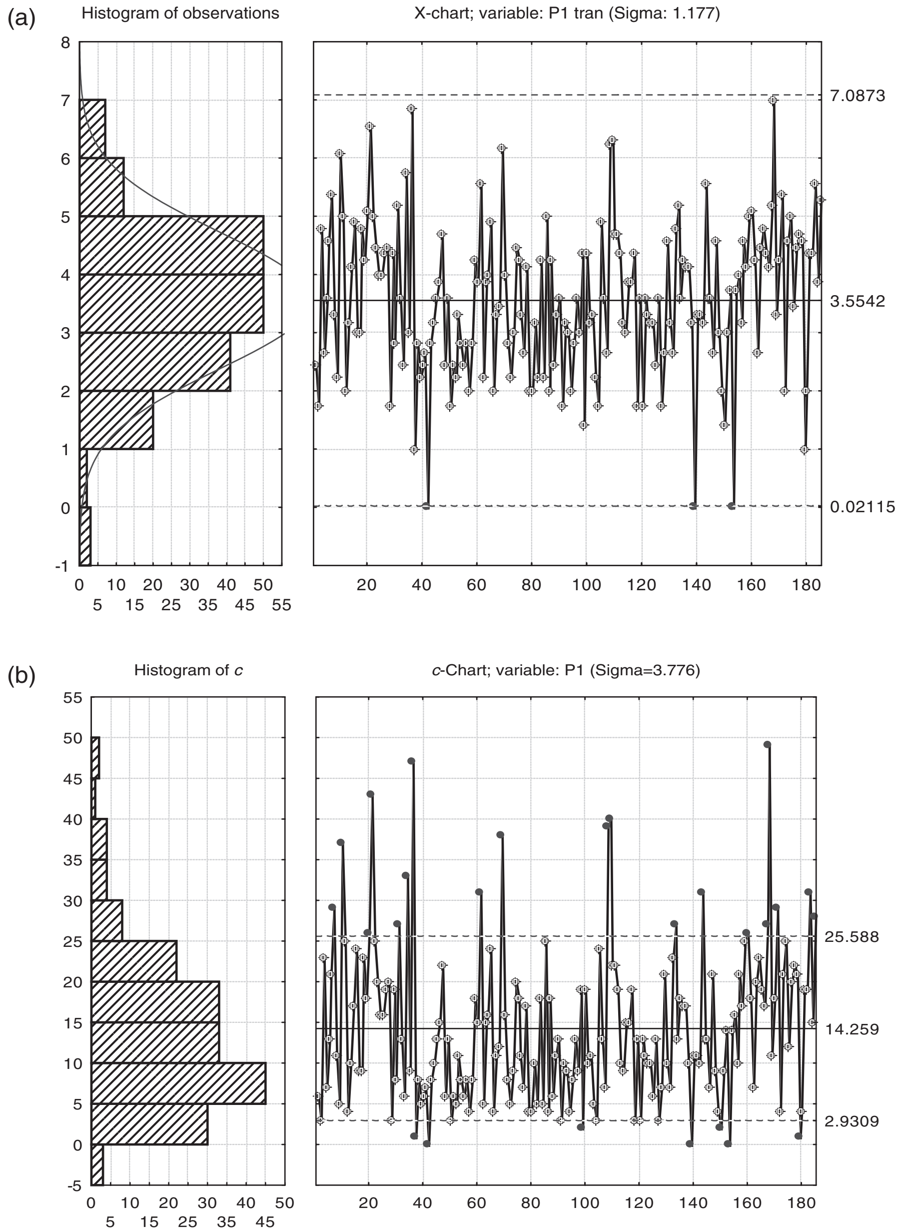


Figure 5. (a) X-chart of machine P1—after data transformation. (b) Standard $c$-chart of machine P1.

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machinery control procedure can reduce the occurrence of false alarms. The Poisson-based control chart is incorrect when defects tend to cluster. The points outside of the control limits may not actually represent the existence of assignable causes in the process. By using the proposed procedure, we can differentiate two types of processes: defect clustering and actual out-of-control.

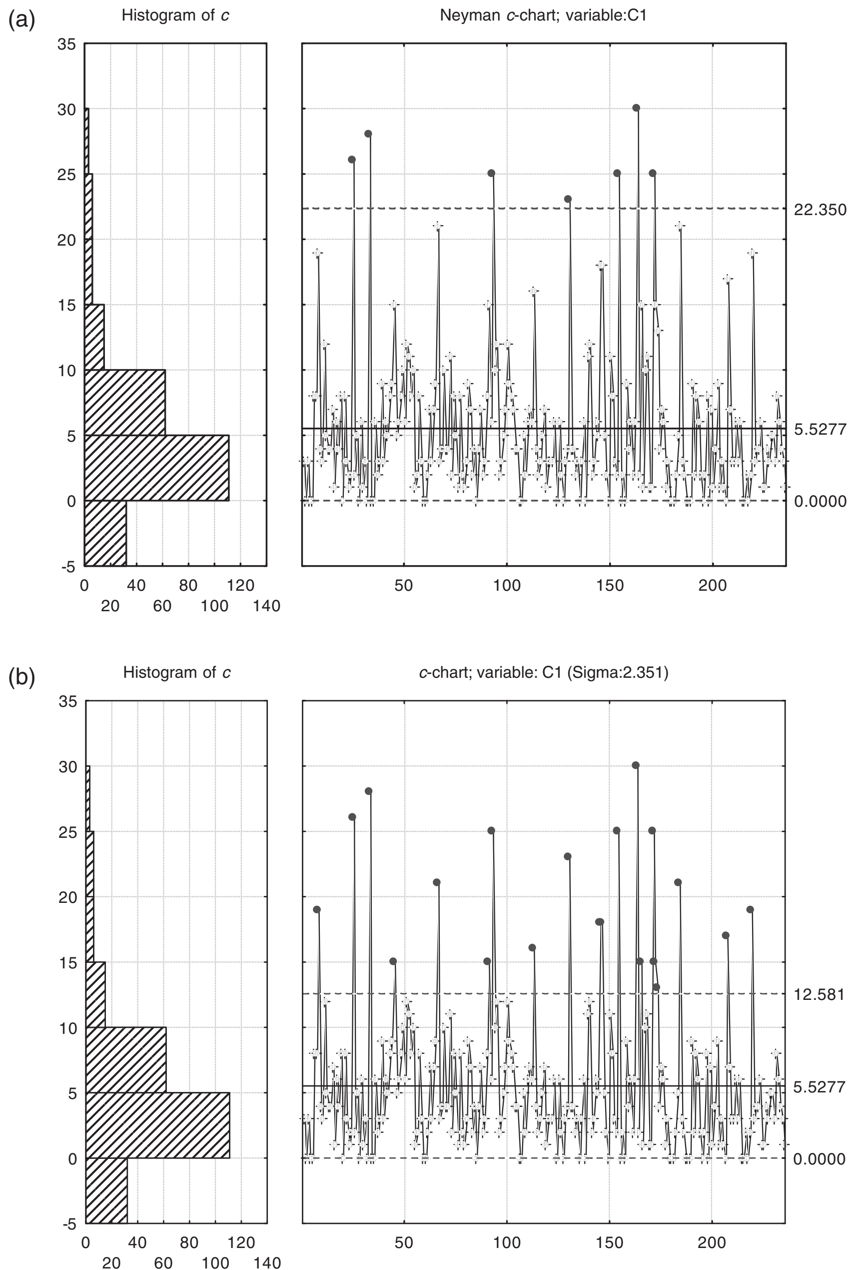


Figure 6. (a) The Neyman based particle control chart of Machine C1. (b) The standard $c$-chart of Machine C1.

## 4.2 *Performance confirmation*

The method developed in this study was implemented in the semiconductor company for four months. During this period, the occurrence rate of false alarms had declined from 20 to 4% (figure 7). Therefore, the method developed in this research can effectively reduce the overly high rate of false alarms resulting

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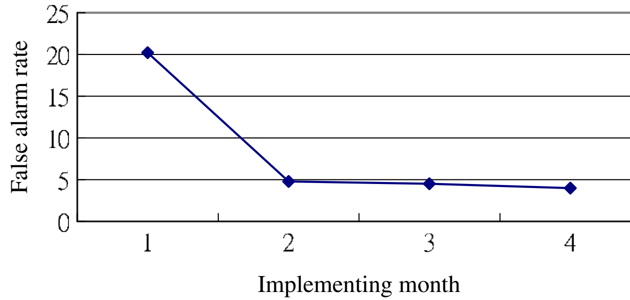


Figure 7. Trend of false alarms rate.

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from the number of particles inconsistent with Poisson distribution. The machinery control method developed in this study can promptly and accurately control machines, reduce defects in wafer production, and thus improve yield and productivity.

## 5. Conclusions

As the size and complexity of semiconductor wafers as well as the precision of processes increase, semiconductor process has reached a degree of 0.1 μm or even smaller. Consequently, the control of the number of particles has become increasingly important. The number of particles on the testing wafer of machines may not satisfy the assumption of a Poisson distribution due to clustering or some other reasons when implementing the *c*-chart control. Continuous use of *c*-charts will result in an overly high rate of false alarms. In this study, a machinery control procedure is developed by primarily combining data transformation and a Neyman type-A distribution. The proposed machinery control procedure can promptly and accurately control the number of particles on the testing wafer of machines. The proposed procedure has the following advantages:

- It is convenient and fast. The parameter estimation of the particle charts based on data transformation and a Neyman type-A distribution does not require complicated formulas. The operating staff can usually calculate the control limits that meet the actual needs of the semiconductor industry easily and quickly.
- Based on the implementation results of an industry empirical case, the occurrence of false alarms has declined from an original 20% to 4%. This implies that the machinery control procedure can effectively resolve the problem of an overly high rate of false alarms and thus accurately monitor the conditions of the machines on semiconductor production line.
- The particle inspection machine has been in existence in the semiconductor industry. Therefore, if the proposed machinery control procedure can be written in computer code and integrated with a particle inspection system, the conditions of the particles on machines along a semiconductor production line can be monitored even more promptly and effectively. An abnormally large number of particles can be recognized and analysed in a timely fashion once it occurs, and the machine can be adjusted accordingly. In this

way, the defects in actual wafer production can be reduced and thus yield can be improved.

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