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Full Length Research Paper

Preventive maintenance model with FMEA and Monte Carlo simulation for the key equipment in semiconductor foundries

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Semiconductor foundries have entered an era of 12-inch wafers and over five hundred production processes involved in manufacturing and measurement. In order to stabilize equipment and reduce variations in processes, an effective equipment maintenance model is required. This study thus aimed to establish a model to maintain the key equipment in a semiconductor factory, based on its history of preventative maintenance (PM) and applying Monte Carlo simulation to predict the probability of the next PM time-point. Focusing on a semiconductor foundry producing RAM, this study found that Chamber2 in the diffusion zone is the key equipment in the FMEA (failure mode and effect analysis), categorized the historical data from various phases to be applied to Monte Carlo simulation, and, with 10,000 simulations and computations, obtained the maintenance time-point probability and the appropriate date for Chamber2 to be the subject of a management review.

Key words: preventive maintenance, Monte Carlo simulation, failure mode and effect analysis (FMEA).

INTRODUCTION

The integrated circuits (IC) produced by semiconductor factories are divided into logic products and memory products. The critical dimensions (CD) of semiconductors have become smaller, and the size of wafers has evolved from 8 inches in 2000 to 12 inches. With larger wafers and smaller CD, the cost and the precision of the related production equipment have increased. In semiconductor factories, the proportion of the manufacturing cost that is directly related to the equipment is quite high, so it is necessary to maintain high utilization and low failure rates(Kuo and Sheu, 2006).

Companies are generally aiming at more reliable production systems with higher availability performance.

Reliability and maintainability play a crucial role in ensuring the successful operation of plant processes as they determine plant availability and thus contribute significantly to process economics and safety. Maintenance and maintenance policy play a major role in achieving systems' operational effectiveness at minimum cost. (Ruiz et al., 2007). In semiconductor foundries, the preventive maintenance (PM) is an important factor to maintaining high utilization of the equipment along with low levels of product failure. The meaning of cumulative generation is similar to the mileage of automobiles, in that, the mileage is constantly increased with operation, and, when a stipulated mileage is reached, maintenance is required.

Within the stipulated period, the time points for maintenance occur randomly. Nevertheless, if the maintenance standards are reached but the production line cannot be stopped, the equipment department is likely to postpone the maintenance. However, if equipment maintenance is not implemented on time, this might result in product failure and seriously affect the production and maintenance plans. For this reason, effectively predicting the equipment preventive maintenance time-point is

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Abbreviations: PM, Preventative maintenance; **FMEA,** failure mode and effect analysis; **IC,** integrated circuits; **CD,** critical dimensions; **RPN,** risk priority number; **CB,** crystal ball.

important for semiconductor factories (Kuo and Sheu, 2006). In previous labor-intensive production patterns, the equipment was simple and the maintenance schedule could be estimated by employees, although there were still chances of incorrect predictions occurring, and different people could make different judgments (Li and Chang, 2002). However, as equipment has become more complex, so the work of maintenance staff has also become more difficult. Consequently, it has become even more important to accurately predict the equipment maintenance time-point in increase efficiency, reduce the maintenance periods, and enhance the availability of equipment so that production is not interrupted.

Regarding the preventive maintenance time-point in semiconductor factories, Kuo and Sheu (2006) applied empirical rules based on human and weighted averages. However, the theoretical basis of their approach was not completely applied, and this meant that the future dynamic states and the regular patterns in the interval sequence could not be effectively found. Although some scholars further applied Grey Theory and genetic algorithm (GA) as the basic theories in related research (Kuo and Sheu, 2006), some problems still remained, such as fuzzy patterns, which could simply predict one maintenance time-point but not all possibilities, so that the manufacturing department and the equipment engineers could not be provided with accurate data on the quantity and dates of equipment repairs. Th aim of this study is thus to find a more appropriate method for analyses. Some scholars have compared the results of using Monte Carlo Simulation with Fuzzy Theory, and found that the former produces better predictions and has more reliability (Wu and Tsang, 2001). In addition, both these methods appear to have favorable effects when used to predict and evaluate the maintenance decisions related to power plants and machinery equipment in ships, as well as to predict their reliability and maintainability (Dong et al., 2003; Cheng et al., 2006). This study therefore utilized failure mode and effects analysis (FMEA) to seek for the key equipment, and further applied Monte Carlo simulation to predict the equipment maintenance time point and evaluate the distribution probability, analyze the cumulative film-thickness in semiconductor factories with a preventive maintenance model, and predict the future time points for preventive maintenance of the equipment, so that the resource plan at the time points can be well-arranged and production will not be significantly disrupted.

LITERATURE REVIEW

Preventive maintenance

Preventive maintenance is a planned maintenance method developed in order to minimize all the operating machines and equipment breakdowns in enterprises to the least extent (Korkut et al., 2009). Maintenance includes operating procedures necessary to maintain or repair a system so that it remains available for use (Pintelon and Gelders, 1992; Blanchard, 1998). Equipment maintenance is classified into two types (Lie and Chun, 1986): (1) corrective maintenance, which means repairs when equipment fails, restoring it to normal function; and (2) preventive maintenance, which is maintenance or replacement that occurs during normal functioning of the equipment, which can restore it to a better functioning condition and reduce the probability of equipment failure, with the maintenance thus a sustained process (Mann, 1983). PM has long been though to be the most effective method to maintain the equipment at optimal functioning (Li and Chang, 2002) and to maintain the highest productive efficiency (Wang and Wang, 2000). Moreover, Wang (2002) also found, from research on equipment maintenance, that an optimized preventive maintenance strategy can improve reliability, prevent the equipment from failure, and reduce the costs due to aging equipment.

For over the past two decades, numerous PM systems have been proposed and studied in various industries (Lim and Park, 2007; Ahire et al., 2000). For instance, Cornell et al. (1987) analyzed the long-term performance of equipment maintenance plans and maintenance policies using the Markov method. Golabi and Shepard (1997) integrated the Markovian prediction with dynamic cost minimization to figure out the optimal construction schedule for road maintenance within a certain budget. Brint (2000) utilized preventive maintenance to find the machinery items which were most likely to cause severe failure. Yao et al. (2004) applied model building and an algorithm to propose an optimal preventive maintenance plan for a semiconductor manufacturing system. All of these previous studies aimed at finding out the best solution to the issue of preventive maintenance in order to reduce uncertainties and further improve production performance. This study has the same aim, although it will use different methods to develop an optimal strategy for the preventive maintenance of semiconductor equipment.

Monte Carlo simulation

Defining the number of samples for statistical analysis in natural resources surveys has always been an important issue (Maeda et al., 2010). To overcome this problem, the presented research carried out a Monte Carlo simulation (Metropolis and Ulam, 1949) prior to the field work. The results of the simulation were used to define the most suitable sampling strategy taking in account the errors inherent in the analysis and the time and resources available for the field work.

Monte Carlo Simulation, which originated from statistical sampling, was first proposed by the physics researcher Maeda and Ulam in 1949. The Monte Carlo method uses random numbers and probability to solve problems by

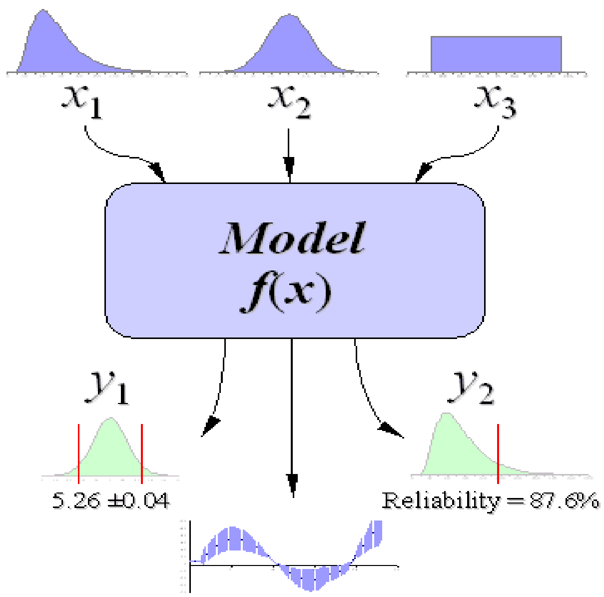

Figure 1. The principal of stochastic uncertainty propagation. (Wittwer, 2004).

directly simulating the process. It may be used to iteratively evaluate a deterministic model using sets of random numbers as inputs (Maeda et al., 2010). A Monte Carlo Simulation requires a lot of random numbers, and so a Random Number Generator is applied when using one. The components of a Monte Carlo Simulation are as follows (Robert and Casella, 2004):

1. Probability density function (p.d.f.), which is a necessary function for physics or mathematics.
2. Random Number Generator, which is the source of random numbers.
3. Sampling prescription, which samples from the assigned p.d.f. with the available unit interval random numbers.
4. Computing, whose output results must be accumulated to a total value.
5. Miscalculation that the estimated frequency for the statistical errors (changes) and the functional relation of other quantity must be determined.
6. Change reduction techniques, which are used to decrease the variances and the computing time for Monte Carlo Simulation.
7. Parallel and vertical integration techniques, so that the implementation of the Monte Carlo Simulation can be effectively applied to advanced computer architecture.

The basic principle of a Monte Carlo Simulation is that it defines a probability density function (p.d.f.) with the probabilities of all possible results, sums up the p.d.f. as a cumulative probability function, and adjusts the maximum value to 1 in a process that is also known as normalization. The p.d.f. is a probability characteristic of the total probability for all events, and it also establishes the connection between the random number sampling and the real problem simulation. With the input of the p.d.f. in the desired simulation, the possible reliability, common differences, and confidence intervals of the real problem can be simulated, as shown in Figure 1. The five simple steps in the Monte Carlo Simulation are as follows (Manno, 1999):

Step 1: Generate a model with parameters, *y = f(x1, x2, ..., xq)*
Step 2: Generate the input of a set of random numbers, *xi1, xi2, ..., xiq*
Step 3: Evaluate the model and save the result, *yi*
Step 4: Repeat Steps 2 and 3, *i* = 1 to *n*.
Step 5: Analyze the statistical results, confidence intervals, and so on.

Random numbers have to be generated at the start of the Monte Carlo Simulation process. Primitive random numbers can be generated with an instance method, such as toss-up, dice, poker, and rotary table, but the drawbacks of these approaches are that they are slow and not possible to replicate. Furthermore, although the random numbers in the random number table produced Rand in 1955 can be replicated, this method is still slow. In addition, when the simulation frequency is large, the table is not big enough. Finally, the Mid-Square Method can be used to select a four-figure number and calculate the square number, or, it can be used to select six-figure or two-figure numbers (Von Neumann, 1981).

The numbers generated from the above methods are merely pseudo-random ones, as they are fixed numbers generated from certain functions (without randomness). In terms of the requirement for random numbers, supposing that the random numbers {1,2,…,m} were the targets, then the generated random numbers should satisfy the requirements of uniform distribution, statistical independence, and replicability (Chaitin, 2001).

Currently, the Linear Congruential Method (LCG) is widely applied. The principle of LCG showed in Equation 1 (Park and Miller, 1998).

$$X_{i+1} = aX(\bmod\ m) \quad (1)$$

a: multiplier
c: increment
m: modulus

Where a, c, m are integers.

Step 1: Given (Seed)

Step 2: $X_1 = aX_0 + c - mK_0$

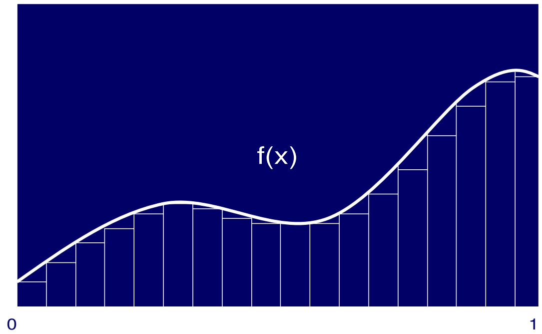

Figure 2. f(x) area measure composed of M equal portions.

Furthermore, most software compound generators, which utilize two or more random number generators to compose a new random number generator (Wichmann and Hill, 1982), are based on Equation 2.

$$x_i = 171 x_{i-1} (\mathrm{mod}\, 30269)$$

$$y_i = 172 y_{i-1} (\mathrm{mod}\, 30307)$$

$$z_i = 170 z_{i-1} (\mathrm{mod}\, 30323)$$

$$u_i = \frac{x_i}{30269} + \frac{y_i}{30307} + \frac{z_i}{30323} (\mathrm{mod}\, 1) \tag{3}$$

With LCG, or other methods, random numbers between 0 and m–1 are generated, these are then divided by m, and random numbers between 0 and 1 are generated that are similar to the random variables U(0 , 1). Other distributions of random numbers can be generated from U(0 , 1), and the characteristics of U(0 , 1) are confirmed with the uniform distribution of the random numbers. By using a fitness test, it can be guaranteed that the random numbers all meet the requirements outlined above. Commonly applied tests include the Chi-square, Goodness-of-fit Test and the Kolmogorov-Smirnov Test, where the former primarily tests the category data. This study applied the Chi-square Goodness-of-fit Test to define the probability distribution (Equation 3):

$$\text{Chi-Square Test } x^2 = \sum_{i=1}^{k} \frac{(o_i - e_i)^2}{e_i} \tag{4}$$

Where *oi* is the observed number and *ei* the theoretical one.

Furthermore, the probability distribution computation used numerical integration in the Monte Carlo Simulation. When integrating a number, the [0 , 1] interval can be easily distinguished (Press et al., 1992), and M-equal portions are evenly divided to compose the area measurement. In the rest of this paper, the computation of the probability for each day is found using the integral method, with the sum being 1, that is, 100%, as shown in Equations 4 and 5.

$$S = \int_0^1 f(x) dx \tag{5}$$

$$S = \frac{1}{M} \sum_{n=1}^{M} f(x_n) + O(1/M^2) \tag{6}$$

In other words, *Xn* could be selected. With the uniform distribution in the random number generator, n = 1 , 2 , ... , *M* are generated, so that, if *M* is big enough, *Xn* becomes a set of the uniform distribution distributed in the region [0 , 1], as in Equations 6 and 7, where *Xn* fluctuates to compose the area measurement (Figure 2).

$$S \approx \langle f_n \rangle = \frac{1}{M} \sum_{n=1}^{M} f(x_n) \tag{7}$$

$$\Delta S = \sqrt{\frac{\langle f_n^2 \rangle - \langle f_n \rangle^2}{M}} \tag{8}$$

Failure mode and effect analysis (FMEA)

FMEA is a reliability analysis for the establishment of a systematic process that, before the implementation of a design/process, looks for all potential problems that may cause failure and provides a risk assessment so that appropriate measures can be applied to eliminate or reduce the risk of such failures (Chen, 2007; Chang, 2009). It's a method of reliability analysis intended to identify failures which have consequences affecting the functioning of a system (Hung and Sung, 2011). FMEA was applied as the analytical approach to the Aircraft Power Plan in the early 1950s, and, based on the requirements of the Automotive Industry Action Group (AIAG, 2008), became one of the five quality system manuals. Nowadays, FMEA is widely applied in many industries, including aviation, automobiles, electronics, semiconductors, and medical equipment (Stamatiis, 1995; Rhee and Ishii, 2003; Chang, 2009). In addition, FMEA is gradually being applied in the service industry, such as in electronic commerce (Linton, 2003). Shahin (2005) further combined it with the Kano model for applications related to tourism.

FMEA is the task of finding possible faults in a system and evaluating the consequence of the fault on the operational status of the system (Hung and Sung, 2011).

Conventionally, the estimation of FMEA utilizes the computation of risk priority number (RPN) (Yeh and Hsieh, 2007), which indicates the severity, frequency of occurrence, and detection of products, shown as RPN=S×O×D, where the severity (S) measures the severity of the impact of a potential failure mode (with customer satisfaction as the overriding concern, and the loss of equipment/personnel being further evaluated); the frequency of occurrence (O), which predicts the frequency of failure factor/structure; and the detection (D), which detects the failure factors or the assessment index of the mode. S, O, and D are all scored with a 1-to-10 grade (AIAG, 2008), with a higher severity, higher frequency of occurrence and a lower detection all meaning a higher score. Furthermore, the Risk Priority Number (RPN) is scored based on the fact that the higher the overall RPN, the more important the failure mode. Previous research indicated that necessary improvement measures should be taken when the RPN is over 100 and S is greater than or equal to 8 (Stamatis, 1995). In addition, after the failure has been addressed, the RPN should be re-calculated to better understand the related reduction in risk and to confirm the effectiveness of the corrections undertaken (Chen, 2007). In conclusion, RPN is often applied to identify potential problems and can be used to undertake a system of active maintenance, so that the management department can both be aware of potential problems and also make predictions as the equipment operating conditions (Almannai et al., 2008).

MATERIALS AND METHODS

Define failure mode and effect analysis (FMEA) to determine the key equipment

This study set the procedure of FMEA and the specifications as follows:

1. To determine the time and the task of FMEA looking for the key equipment.
2. Based on the equipment or the functional characteristics, the task group is set up, appropriate personnel are selected, and they are effectively integrated. The number of members in the task group depends on the task, but generally three to seven qualified personnel are selected from each department. The task supervisor is in charge of coordinating and instructing the participants with regard to the division of labor and individual responsibilities, as well as reporting on the operating conditions.
3. To carry out the failure mode and effect analyses using the FMEA published by the Automotive Industry Action Group (AIAG).
4. All possible potential failure modes should be taken into account in the analyses, and the discussions should be undertaken from the perspectives of customers, who in this case are the maintenance personnel, process engineers, assembly design engineers, test engineers, and product analysts.
5. The effects of all possible potential failure modes with regard to delays, damage, and safety should be noted.
6. The situation at both the start and end of the process should be examined to find out the effects and the factors related to the corresponding failure modes.

In order to document the potential failures and carry out the effects analyses, an FMEA format was defined specifically to determine the key equipment. After interviews with the deputy manager in the equipment department, the table and the severity, frequency and detection grading standards were defined with regard to semiconductor equipment. The key equipment was thus determined using the definitions of the 16 FMEA items and filling in a related form, as follows:

1. FMEA number. Filling in the FMEA document number for inquiries and filing.
2. FEMA project name. In this study, FMEA is used to evaluate key equipment performance.
3. Process liability. Filling in the entire factory or the department and the team.
4. Editor. Filling in the name and the department of the engineer in charge of the preparations for FMEA.
5. Key date. Filling in the first scheduled finish date for FMEA.
6. FMEA dates. Filling in the initial date of editing FMEA and the revision date.
7. Core team. Listing the authorized and task-implementing department and the individuals.
8. Function requirements. Briefly describing the analyzed equipment and the model, as well as explaining the functions of the equipment.
9. Potential failure mode. After listing the possible failures of the equipment, the failure mode should be proceeded to conclude the related factors.
10. Potential failure effects. The possible effects of failure modes on the production line, the product quality, and the customers are stated.
11. Severity. When a potential failure mode occurs, the grading of severity of the effects on the next procedure (production line, product quality, and customers) is defined as in Table 1.
12. Potential factors in failure. Listing all possible factors in equipment failure and the related potential failure effects.
13. Frequency of occurrence. Scoring the possibility of the specific factors related to equipment failure, as defined in Table 2.
14. Current control. The current control methods to prevent the equipment from failure modes that preventive maintenance of the equipment is the current control mechanism.
15. Detection. A method to detect the failure of the equipment. Generally, the foundry applies Advance Process Control (APC) to receive the equipment signals to detect and monitor the equipment conditions, as defined in Table 3.
16. Improvement of risk priority number. Multiplying the severity, the frequency of occurrence, and the detection to be the RPN of the equipment.

The above items are written on a blank form, with a focus on the equipment in each department. The equipment with highest RPN overall is considered as the key equipment, with a greater risk to operations if not stable.

A maintenance prediction model with a Monte Carlo Simulation

After the key equipment has been identified confirmed, the historic data of the equipment maintenance values are simulated. First of all, the characteristics of the rises in equipment values were studied; the operating function is set with in relation to the function of the time and the equipment values; α_i is defined as the equipment value of this maintenance action, and β_i the time (unit: day) from the previous action to this one; and, with the relation function of α_i

Table 1. Severity grading.

Effect	Decision criteria: severity of the effect	Severity
Severe crisis	Possible harm to the equipment or the maintenance personnel, does not conform to government regulations, and no warnings at failure	9-10
Very high	Customer complaints about product quality that affect shipments or causes rejected products.	7-8
Medium	Does not severely affect the production line, and affected products can be reworked.	5-6
Very low	Only slightly affects the production line, but will still affect product quality.	3-4
Very slight	Only slightly affects the production line, but does not affect product quality.	1-2

Table 2. Frequency grading.

Effect	Decision criteria: possibility of failure	Frequency of occurrence
Very high	Inevitable equipment failure.	9-10
High	Often occurs, about once a month.	7-8
Medium	Seldom occurs, once every half-year or a season.	5-6
Low	Occurs once or more per year.	3-4
Very low	Hardly ever occurs.	1-2

Table 3. Detection grading.

Effect	Decision criteria: Possibility of detection	Frequency of occurrence
Very difficult	Cannot be detected and not until the defective product is detected will the equipment failure be found, so that several lots of defective products will already have been produced.	9-10
Difficult	Cannot be detected and not until the defective product is detected will the equipment failure be found, so that one lot of defective products will already have been produced.	7-8
Medium	At detecting conditions to receive the equipment signals, without defined control limits so that the failure equipment is not automatically held.	5-6
Easy	At detecting conditions to receive the equipment signals, with defined control limits but the failure equipment is not automatically held.	3-4
Very easy	At 100% detecting conditions to receive the equipment signals, with defined control limits that the equipment failure is automatically detected.	1-2

and β_i, the rise in the equipment values in a unit day is obtained as *S*(*x*), as in Equation 8.

$$S(x) = \alpha_i / \beta \; ; \; \alpha_i \geq 0; \beta_i > 0 \tag{9}$$

The minimum rise of all rises in a unit day from the first maintenance action to the i^{th} maintenance is defined as *S*(*a*) (Equation 9).

$$S(a) = \min\left[\alpha_1 / \beta_1, \ldots, \alpha_i / \beta_i\right] \; ; \; \alpha_i \geq 0; \beta_i > 0 \tag{10}$$

The maximum rise of all the rises in a unit day from the first to the ith maintenance is defined as *S*(*b*), (Equation10).

$$S(b)=\max\left[\alpha_1/\beta_1,\ldots,\alpha_i/\beta_i\right]\ ;\ \alpha_i\geq 0;\beta_i>0 \quad 11$$

The average rise of all rises in a unit day from the first maintenance to the ith maintenance is defined as *S*(*c*) (Equation11).

$$S(c)=\bar{c}=\frac{1}{N}\sum_{i=1}^{N}\left(\alpha_i/\beta_i\right)\ ;\ \alpha_i\geq 0;\beta_i>0 \quad 12$$

The standard deviation of all rises in a unit day from the first maintenance to the ith maintenance is defined as *S*(*d*) (Equation 12).

$$S(d)=\sigma=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[(\alpha_i/\beta_i)-S(c)\right]}\ ;\ \alpha_i\geq 0;\beta_i>0 \quad 13$$

The first maintenance value is defined as PM_i, with the ith maintenance value as PM_i. The maximum value from the predictions, defined as *S*(*e*), is used to select the closest value from the first to the ith maintenance values as the target, where the predictions are shown as in Equation 13.

$$S(e)=\max\left[PM_1,\ldots,PM_i\right] \quad 14$$

S(*K*) is defined as the average maintenance interval, and is used for the prediction of maintenance time-points as well as the important output analyses, as shown in Equation 14.

$$S(K)=S(e)/S(c) \quad 15$$

S(*M*) is defined as the most likely maintenance interval, and is compared with *S*(*K*) as well as determine the longest possible period between maintenance actions (days), as in Equation 15.

$$S(M)=S(e)/S(a) \quad 16$$

S(*N*) is defined as the shortest possible maintenance interval in days, in comparison with *S*(*K*), as in Equation 16.

$$S(N)=S(e)/S(b) \quad 17$$

Having established the maintenance prediction model, the computation was solved using a probability model in the Monte Carlo Simulation. Based on the historic data or the probability distribution of the factors, the distributed parameters were estimated, and, with the random variables of the parameters, Crystal Ball (CB) software was applied for the analyses. The random number generator of the software CB applied LCG and was run for 10,000 tests, and thus this study could obtain the probability distribution of maintenance time-points, with the radius of the error range of the system confidence interval (CI) set at 95%, as in Equation 17.

$$P(-z\leq Z\leq z)=1-\alpha=0.95 \quad 18$$

Based on the results of the maintenance prediction model, above, this next subsection discusses of the probability density function presented in the accumulated data. The time-line is studied first. According to the data, when the productivity of a foundry is steady the value is quantitatively accumulated, and the resulting per-unit-day rise is steady and without much variation, so that the probability distribution of the rate of increase follows a normal distribution. Furthermore, the average rise within a day collected from several maintenance cycles is calculated using the average *S(c)* and the standard deviation *S(d)*, input to Crystal Ball (CB), in order to establish the Monte Carlo simulation with the accumulated rises (Figure 3).

To simulate the escalating trend probability distribution models of the accumulative generated values foundries are likely to define the target value and the upper and the lower limits. The lower limit is the management control that triggers an alerting when the equipment requires maintenance, while the upper limit is generally not exceeded as it might adversely affect product quality, and further result in equipment failure. The real values of the foundry show that the escalating trend probability distribution has a triangular distribution. Simulating the escalating trend input to CB, the Monte Carlo Simulation for the rise of each items of historic data are established, as shown in Figure 4.

When the distribution probability is generated, the maximum generation *S(e)* is selected from to in the simulation and then divided by the one-day rise in the Monte Carlo Simulation, so that the predicted distribution of time points can be calculated and further divided by *S(a)* or *S(b),* and then, the predicted distribution of the longest and shortest periods can be calculated.

Based on the historic maintenance data, a sensitivity analysis is further implemented to evaluate the contribution of various maintenance actions to the entire system maintenance. The accumulative characteristics of the equipment with better representativeness in the simulation are listed, and the equipment distribution test applies Chi-square Goodness-of-fit Test of nonparametric statistics in the CB software to model of the target probability distribution, and a discussion of the parameter is not required. This method is similar to the statistical inference method, which looks for the most appropriate probability distribution. The ultimate target of the current study is to select the top three PM dates for use as a management referral index.

RESULTS

This research aimed to produce an effective PM model in the diffusion zone (equipment coded with the initial "D") of a semiconductor foundry for computer memory in Taiwan. In the period of data collection, data were collected on the production conditions in a foundry with a fixed production of 60,000 wafers every month, without considering the factors of installing new equipment or decreasing production, and the preventive maintenance model being based on cumulative wafer thickness. The discussion presented in this work covered the FMEA of the key equipment in various departments of the semiconductor foundry. The key determinants examined were the RPN being over 100, and the severity equal to or more than 8.

As noted earlier, when completing the FMEA for the key equipment, an RPN over 100 and S larger than or equal to

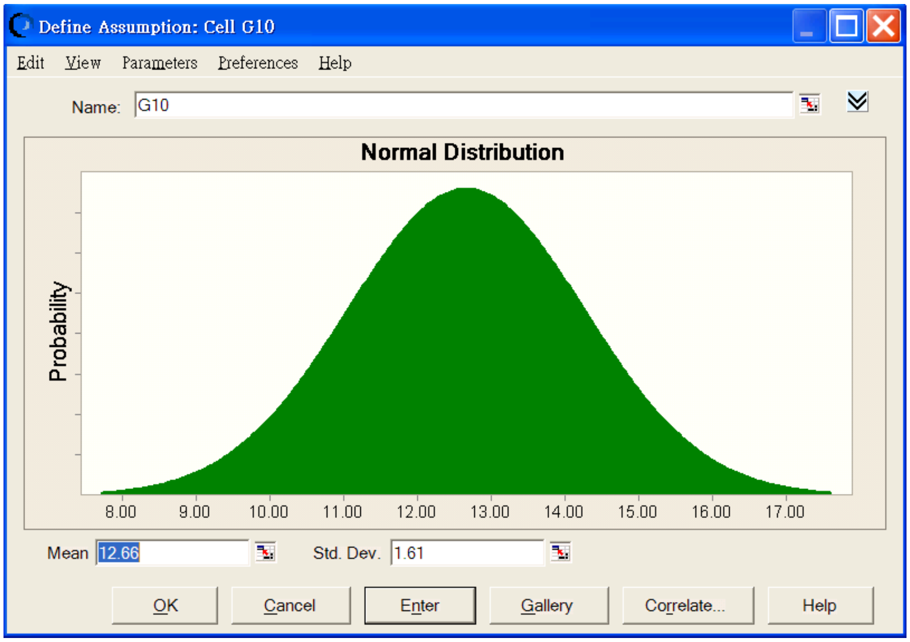

Figure 3. Crystal Ball-defined normal distribution.

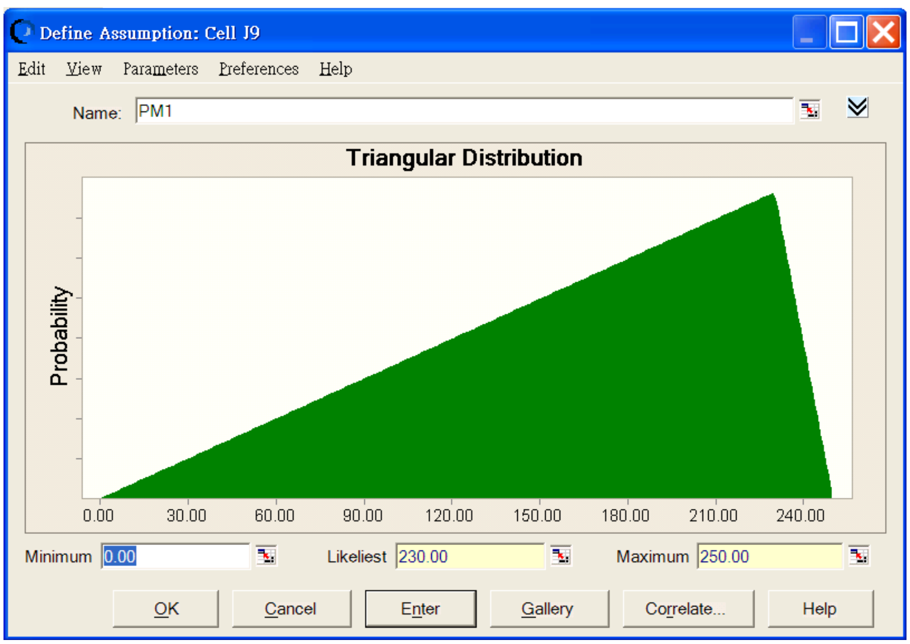

Figure 4. Crystal Ball-defined triangular distribution.

8 (Stamatis, 1995) were applied as the decision criteria for the key equipment. This study then analyzed the FMEA of the equipment failure records with regard to thin film, etching, diffusion, chemistry mechanistic polish, and cleaning. Table 4 shows part of the relevant equipment analyses, in which DX-XXX-03-CH2 is determined as the key equipment. The equipment data were then collected to set the conditions for the simulation model, and after the prediction was completed the results of the simulation were analyzed. After confirming that the equipment coded DX-XXX-03-CH2 (CH2 represents the second chamber) is the key equipment in the diffusion zone, the relevant data within the period of December 6th, 2009 to March 3rd, 2010 were obtained, and eight PM were conducted in

Table 4. FMEA Analysis of the semiconductor equipment.

Equipment failure mode and effects analysis								
Item: Key equipment assessment **Key Date: 2009/12/06**		**Process department: All Eq. Dept** **FMEA Date: 2009/12/07**				**FMEA No.:0001** **Prepared By: XXX** **Core Team: Eq. Team**		
Function Requirements	Potential Failure Mode	Potential Effects of Failure	S	Potential Causes /Mechanism of Failure	O	Current Process Control	D	RPN
ETCH EX-XXX-02-CH2	Product over ETCH	Shipping to customer lead to customer complains, and Yield loss 20%.	*8	Equipment Etch time abnormal	3	Receive and detect equipment message, define control Spec., but cannot auto hold equipment when abnormal.	4	96
ETCH EX-XXX-02-CH3	Equipment down	Product reworks 10 pcs.	5	Equipment PCB broken	2	Receive and detect equipment message, but cannot auto hold equipment when PCB broken.	6	60
DIFF DX-XXX-03-CH1	Equipment down	Effect production, and lead to shipping.	3	Unclear equipment issue	4	100% receive and detect equipment message, auto hold equipment when abnormal happen.	2	24
DIFF DX-XXX-03-CH2	Implant dose abnormal	Customer complains, the issue lead to Yield loss 30%.	*8	Implanter broken, and did not notice	2	It cannot detect until product happen abnormal.	9	*144
TF TX-TXX-04-CH3	NH4 gas leak	Damage equipment or operator.	*9	Equipment pipe broken	2	To receive and detect equipment message.	3	54

Table 5. Cumulative film-thickness of DX-XXX-03-Chamber2.

	PM data (2009/12/6~2010/3/3)							
PM times	1	2	*3	4	5	*6	7	8
PM interval (day)	9	12	7	8	9	7	13	9
Cumulative film-thickness (nm)	23.94	24.98	17.85	25.58	22.63	19.57	26.91	27.32

* Failure maintenance without reaching the cumulative film-thickness of 22-28 nm.

the period. The PM time occurred when the equipment processing chamber reached 25 cumulative film-thicknesses, and so this value was the key for PM, but the maintenance was not necessarily conducted at this point. Since the equipment was perhaps stopped for maintenance without completing a shipment of wafers, the actual value was about three cumulative film-thicknesses more or less than 25 nm. Indeed, it was also suggested by the equipment manufacturer that maintenance should be implemented at 22-28 nm cumulative film-thicknesses. The sorted data are shown in Table 5.The data in Table 5 were used in the algorithm model in this study, and further set in the

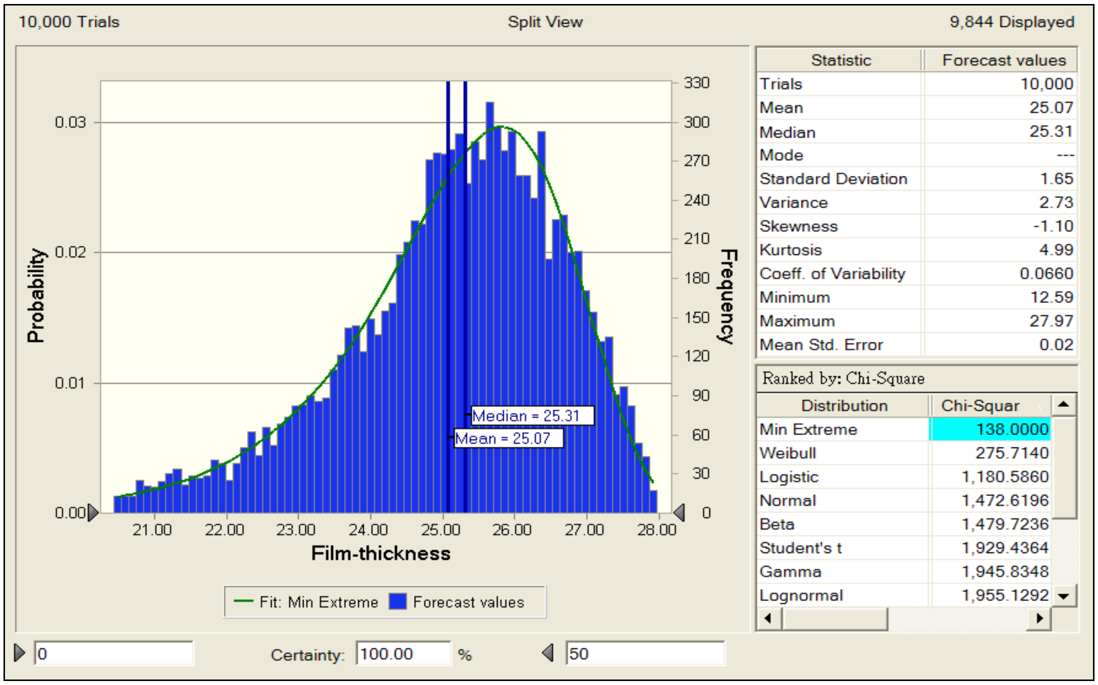

Figure 5. Cumulative film-thickness value simulation distribution.

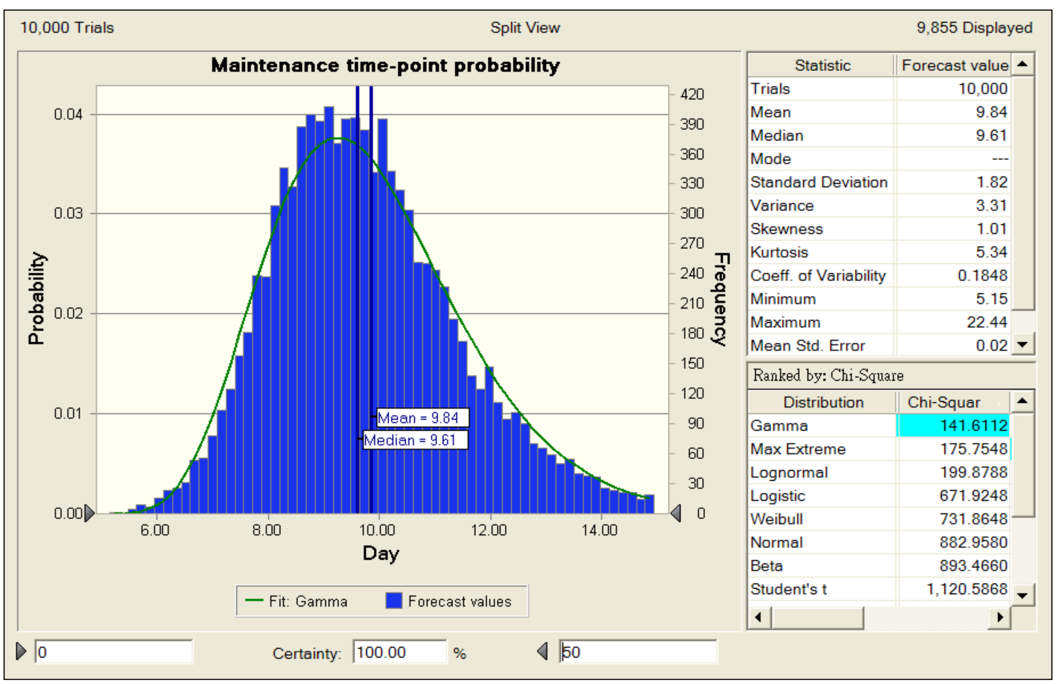

Figure 6. Maintenance time-point probability distribution of the cumulative wafer thickness equipment.

simulation software CB. In addition, the confidence interval was set at 95%, and the Monte Carlo Simulation was run 10,000 times to obtain the simulated distribution of the 10,000 values and the relevant data, as shown in Figure 5. With the test distribution approaching Min Extreme, the average value of 25.07 nm cumulative

Table 6. Probability of time-point for maintenance action.

Period	Probability (%)	Period	Probability (%)
Days 0~6	2.57	Day 11	11.4
Day 7	10.10	Day 12	5.63
Day 8	22.13	Day 13	2.92
Day 9	24.20	Day 14~∞	2.34
Day 10	18.71	Total	100.00

film-thicknesses was divided by the rise of the one unit-day value within PM1 to PM8 combined withthe Monte Carlo Simulation Model in this study. The ordinary maintenance period probability distribution of the equipment *S*(*K*), simulated with the Monte Carlo Simulation, is shown as Figure 6. The average maintenance cycle was 9.84 days, and the test distribution approached Max Extreme. The standarddeviation of the output data with further analyses was 1.82, and the standard error of the mean (SEM) was 0.02, representing the considerable reliability of the conclusion. This simulation was random number generated and based on the central limit theorem (Hayter, 1996). The simulations in this study were run up to 10,000 times, so that the results approached normal distribution. Applying the simulation with a known average standard deviation to implement a two-sample t-test on the historic data (α<0.05 was set as the statistical difference), the t-value was -0.07 (p-value =0.467 ; 95 CI%=-2.424283, 1.234495), meaning that the model produced a predicted maintenance period that had no significant differences with the reality. The probability percentage calculated for every day is shown in Table 6, which reveals that the most likely number of days between maintenance actions is nine, with the probability of 24.2%. This study aimed to select the top three most likely periods, and the results show that the eighth and tenth days were the dates when PM was most likely to occur, and this can be used as a reference by managers.

With the set model to calculate the shortest *S(N)* and longest *S(M)* possible periods between maintenance actions, and the probability distribution and the relevant data are shown in Figures 7 and 8, respectively, and a comparison of these is shown in Figure 9. The comparison enables us to accurately define the shortest period as 7.97 days and the longest as 12.61.

The simulation in this study was run 10,000 times. The data for the PM maintenance time-points produced based on the model in this work were further confirmed with the two-sample t-test, the results of which showed the similarity between the simulation and reality. According to the accumulative generations of the five pieces of equipments, the PM period in the historic data also contained failure maintenance actions, but these did not affect the simulated overall probability distribution or the average. For instance, in terms of the PM of the cumulative films from the DX-XXX-03-Chamber2, the eight maintenance actions in the historic data had an average interval of 9.84 days, and two failure maintenance actions were included in the historic data that was one-quarter of the data. The values on the seventh day were 17.85 and 19.57, which were far less than the specification of 25 nm. The simulation result on the seventh day presented low probability of 10.1%, asshown in Table 6, as the rises in equipment value was defined as the computing basis with one unit-day, as shown in Equation 8, and further computed with random number generations so that the simulation would not be inclined to the right or the left distribution resulting from failure maintenance or the maintenance period, respectively. According to the sensitivity analyses in this study, the PM with the highest probability simply stood for the cumulative characteristic at the time of the simulation. With the verification, the largest contribution of the PM obtained from the 10,000 simulations was different. The uniform distribution generated from the Monte Carlo Simulation's random numbers therefore demonstrated that the probability of the simulations at any PM period was equal.

CONCLUSION

Research on the maintenance and reliability of the equipment in semiconductor factories is increasing (Degbotse and Nachlas, 2003; Kuo and Sheu, 2006). As the precision and the size of the equipment in such factories are increasing, the maintenance and reliability of this equipment is of critical importance. By using empirical research, this study aimed to provide foundries with the data needed to know when to best maintain its key equipment.

This study proposed using FMEA and a Monte Carlo Simulation to predict the time-points for preventive maintenance. With FMEA, a systematic record clearly highlighted the key or bottleneck equipment in the semiconductor foundry for the reference of the equipment engineering department. In terms of FMEA verification, the chemistry mechanistic polishing and cleaning in the case-studied semiconductor foundry were not the zones with the key equipment, as the RPN did not reach the level of 100 and the severity not equal to or larger than 8. On the other hand, Chamber2 in the diffusion zone had an RPN of 144, and thus can be considered as a key piece of equipment. In this case, not all processing zones had similar failure occurrence probabilities and severities, but some processing zones were more likely to have serious effects if a failure occurred, and thus the engineering and the equipment departments should pay more attention to these. Having found the key equipment, a Monte Carlo Simulation was further applied to predict the equipment's PM time-point so as to achieve the characteristics of

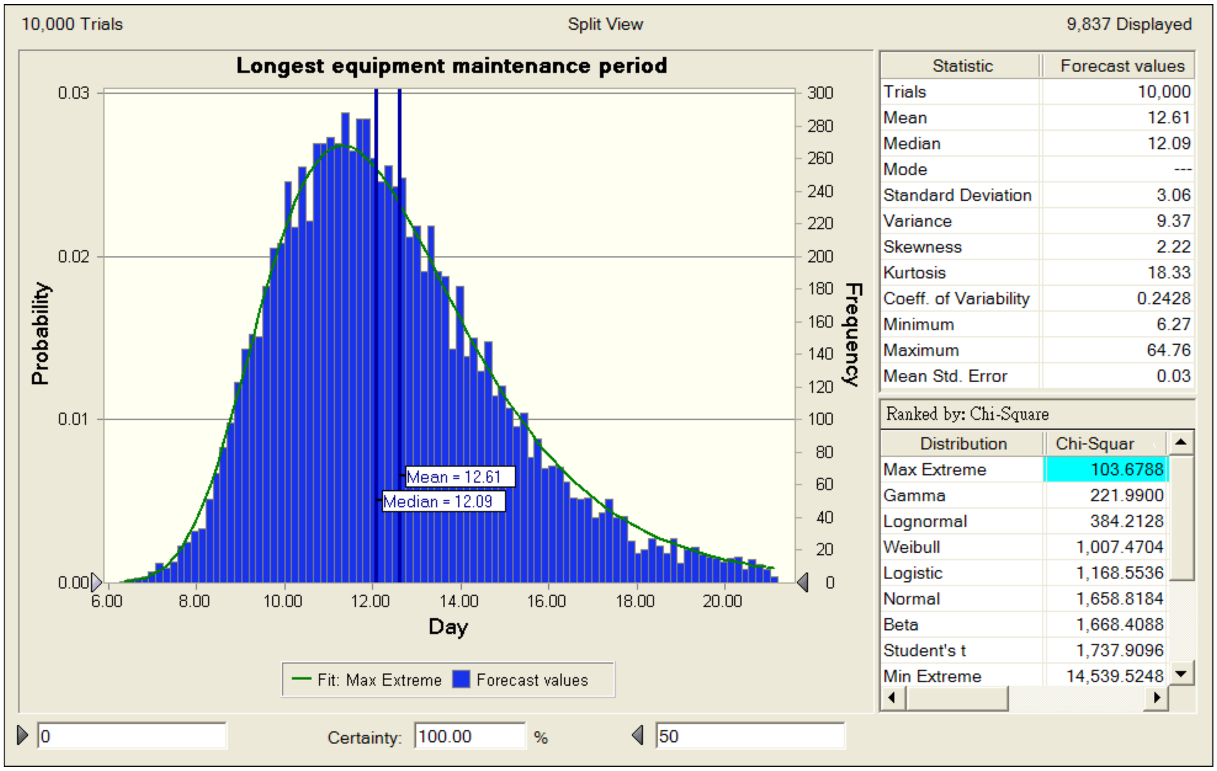

Figure 7. Probability distribution of the longest equipment maintenance period for cumulative film-thickness.

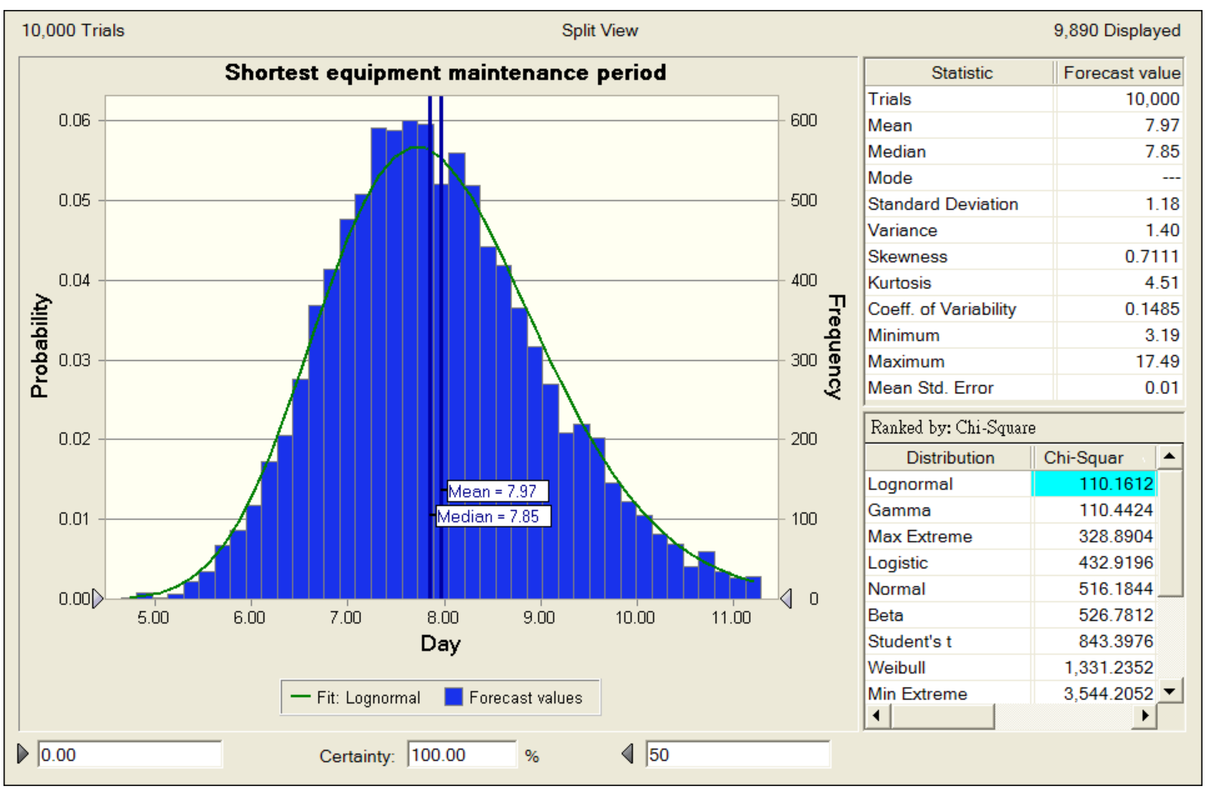

Figure 8. Probability distribution of the shortest equipment maintenance period for cumulative film-thickness.

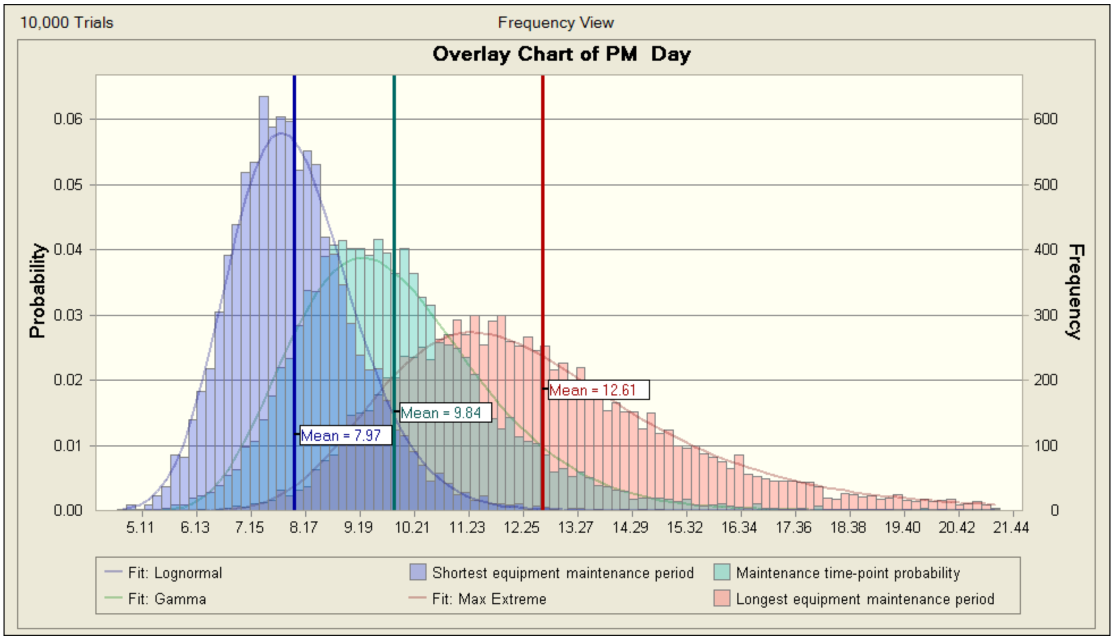

Figure 9. Comparison of the probability distributions of the combined maintenance time-points for cumulative film-thickness.

cumulatively generated data of PM in semiconductor factories that general algorithm could not achieve, complete the data with various periods, apply the set mode to complete an entire cycle which contained the average and the standard deviation calculated from the 10,000 simulations, as well as generate the probability of each day and the most probable p.d.f. of the maintenance time-point. With these predictions, this study computedthe probability of each date so as to enhance the accuracy of the results, which can then be used by managers when making places for the arrangement of manpower, machines, and materials. In addition, these results could also be used to reduce the chance of the equipment department re-scheduling actions and postponing the maintenance.

According to the results of this study, businesses could establish an effective maintenance model, standardize a regular maintenance plan and the maintenance arrangement and prediction, provide the setting control and the alerting specifications as the referral index of maintenance time-point for the manufacture and the equipment engineering departments, and achieve the objectives of the semiconductor manufacturing management (Chien et al., 2004) that the Overall Equipment Efficiency (OEE) of the world standard > 85% with high production efficiency, high equipment stability, high bottleneck equipment efficacy, and high equipment utilization. With the predicted results, this study established the period control limit for the alert so that the equipment department could establish the maintenance time-point for the periodical control.

REFERENCES

Ahire S, Greenwood G, Gupta A, Terwilliger M (2000). Workforce-constrained preventive maintenance scheduling using evolution strategies. Decis Sci., 31(4): 833-858.

AIAG (2008). Reference manual: potential failure mode and effects analysis (FMEA), 4th, USA, AIAG.

Almannai B, Greenough R, Kay J (2008). A decision support tool based on QFD and FMEA for the selection of manufacturing automation technologies, Robotics and Comput. Integr. Man., 24(4): 501-507.

Blanchard BS (1998). Logistics Engineering and Management, Prentice-Hall International, Inc.

Brint AT (2000). Sequential inspection sampling to avoid failure critical items being in an at risk condition. J. Operat. Res. Soc., 51(9): 1051-1059.

Chaitin GJ (2001). Exploring Randomness. London: Springer-Verlag.

Chang KH (2009). Evaluate the orderings of risk for failure problems using a more general RPN methodology. Microelect. Reliab., 49(12): 1586-1596.

Chen JK (2007). Utility Priority Number Evaluation for FMEA. J. Failure Anal. Prevent., 7(5): 321-328.

Cheng WX, Chen LQ, Gong SG, Ding YZ (2006). Readiness simulation of ship equipment based on Monte-Carlo method. Acta Armamentarii, 27(6): 1090-1094.

Chien C, Hsiao A, Wang I (2004). Constructing Semiconductor manufacturing performance index and applying data mining for manufacturing data analysis. J. Chin. Instit. Ind. Eng., 21(4): 313-327.

Cornell P, Lee H, Tagaras G (1987). Warnings of malfunctions: The decision to inspect and maintain processes on schedule or on demand. Manage. Sci., 33(10): 1277-1290.

Degbotse AT, Nachlas JA (2003). Use of Nested Renewals to Model Availability Under Opportunistic Maintenance Policies. The J. Proc. Ann. Reliab. Maintainab. Symposium., 6: 344-350.

Dong YL, Gu YJ, Yang K (2003). Critically analysis on equipment in

power plant based on Mote Carlo simulation. Proc. Chin. Soc. Elect. Eng., 23(8): 201-205.
Golabi K, Shepard R (1997). Pontis: A system for maintenance optimization and improvement of US bridge networks. Interface, 27: 71-88.
Hayter JA (1996). Probability and Statistics for Engineers and Scientists. Boston: PWS publishing company.
Hung HC, Sung MH (2011). Applying six sigma to manufacturing processes in the food industry to reduce quality cost. Scientific Research and Essays. 6(3): 580-591.
Korkut DS, Bekar I, Oztekin E (2009). Application of preventivemaintenance planning in a parquet enterprise. Afr. J. Biotechnol., 8(8): 1665-1671.
Kuo JY, Sheu DD (2006). A Forecasting Model for Semiconductor Equipment Preventive Maintenance. J. Occupat. Safety Health., 14(2): 124-132.
Li CH, Chang SC (2002). A preventive maintenance forecast method for interval triggers. The Journal of IEEE Trans. semiconduct. Man., pp. 275-277.
Lie CH, Chun YH (1986). An algorithm for preventive maintenance policy. IEEE Trans. Reliab., 35(1): 71-75.
Lim JH, Park DH (2007). Optimal periodic preventive maintenance schedules with improvement factors depending on number of preventive maintenances. Asia-Pacific J. Operat. Res., 24(1): 111-124.
Linton JD (2003). Facing the challenges of service automation: An enabler for e-commerce and productivity gain in traditional services. IEEE Trans. Eng. Manage., 50(4): 478-484.
Mann LJr (1983). Maintenance Management. Lexington Books. New York.
Manno I (1999). Introduction to the Monte Carlo Method, Budapest: Akademiai Kiado.
Maeda EE, Pellikka P, Clark BJF (2010). Monte Carlo simulation and remote sensing applied to agricultural survey sampling strategy in Taita Hills, Kenya. Afr. J. Agric. Res., 5(13): 1647-1654.
Metropolis N, Ulam S (1949). The Monte Carlo Method. J. Am. Stat. Assoc., 44(247): 335-341.
Park SK, Miller KW (1988). Random number generators: good ones are hard to find. Communications of the ACM, 31(10): 1192-1201.
Pintelon LM, Gelders LF (1992). Invited review: maintenance management. Eur. J. Operat. Res., 58: 301-17.
Press WH, Flannery BP, Teukolsky SA, Vetterling W T (1992). Numerical Recipes in FORTRAN 77: The Art of Scientific Computing. 2nd. Cambridge University Press.
Rhee SJ, Ishii K (2003). Using cost based FMEA to enhance reliability and serviceability. Adv. Eng. Inf., 17(3-4): 179-188.
Robert CP, Casella G (2004). Monte Carlo Statistical Methods. 2nd. London: Springer-Verlag.
Ruiz R, García-Díaz JC, Maroto C (2007). Considering scheduling and preventive maintenance in the flowshop sequencing problem. Comput. Operat. Res., 34: 3314-3330
Shahin A (2005). Integration of FMEA and the Kano model: An exploratory examination. International J. Quality Reliab. Manage., 21(6/7): 731-746.
Stamatis DH (1995). Failure mode and effect analysis: FMEA from theory to execution. ASQC Quality Press. Milwaukee. WI.
Von Neumann J (1981). The Principles of Large-Scale Computing Machines. Ann. History Comput., 3(3): 263-273.
Wang EJ, Wang LW (2000). Industrial Engineering and Management. Hwa-Tai Publishing. Taipei.
Wang HZ (2002). A survey of maintenance policies of deteriorating systems. Eur. J. Operat. Res.. 139(3): 469-489.
Wichmann BA, Hill ID (1982). An efficient and portable pseudo-random number generator. Appl. Stat., 31(2): 188-190.
Wittwer JW (2004). Monte Carlo Simulation Basics. From Vertex42.com. June 1, 2004. http://vertex42.com/ExcelArticles/mc/MonteCarloSimulation.html
Wu FC, Tsang YP (2001). Comparison of Fuzzy and Monte Carlo methods in uncertainty analysis of salmonid Embryo survival. J. Chin. Agric. Eng., 47(4): 48-55.
Yao X, Fernandez-Gaucherand E, Fu M, Marcus SI (2004). Optimal preventive maintenance scheduling in semiconductor manufacturing. IEEE Trans. Semiconduct. Man., 17(23): 345-356.
Yeh HR, Hsieh MH (2007). Fuzzy assessment of FMEA for a sewage plant. J. Chin. Instit. Ind. Eng., 24(6): 505-512.