DEVELOPMENT OF SEQUENTIAL ASSOCIATION RULES FOR PREVENTING MINOR-STOPPAGES IN SEMI-CONDUCTOR MANUFACTURING

Sumika Arima, Ushio Sumita and Jun Yoshii

Graduate School of Systems and Information Engineering, University of Tsukuba
Tennoudai 1-1-1, Tsukuba, Ibaraki 305-8573, Japan

Keywords: Semi-conductor manufacturing, Minor-stoppages, Sequential association rules, Preventive maintenance policies.

Abstract: In semi-conductor manufacturing, the machine downtimes due to minor-stoppages often exceed 40% of the working hours of a day, and would amount to the huge loss. However, effective methodological tools for predicting and preventing the minor-stoppages are hard to come by. The purpose of this research is to fill this gap by establishing effective preventive maintenance policies for controlling minor-stoppages. Our approach is to develop association rules based on sequential data along the time axis so that the resulting rules could be used for predicting occurrences of certain minor-stoppages. The proposed methodology is applied to a real data set and yields two preventive maintenance policies in a concrete form, thereby demonstrating its power and usefulness. While the paper focuses on the testing process, the methodology proposed in this paper is valid for other production processes, provided that similar sequential data could be collected.

1 INTRODUCTION

Semi-conductor manufacturing is characterized by a sequence of sophisticated manufacturing processes, often exceeding several hundred production steps. Such processes possess both aspects of continuous and discrete operations. On one hand, many production steps involve chemical diffusion for etching layers of circuits and such steps ought to be controlled continuously. On the other hand, the final products are semi-conductor chips which are clearly discrete in nature. Combined with necessary ultra-precision technologies, these factors make semi-conductor manufacturing extremely difficult to control and force one to rely upon quite expensive automated production machines. Accordingly, the cost of machine downtimes in semi-conductor manufacturing is quite huge. When a major failure of a production machine occurs, vender engineers have to be often called in and the repair may sometimes take more than a few days.

Apart from such major failures, in semi-conductor manufacturing, the machine downtimes due to minor-stoppages would also amount to the huge loss. A minor-stoppage is defined to be a machine failure which requires the direct involvement of an operator for repair but the repair time is quite short once the problem is addressed by the operator. Frequency of minor-stoppages is typically quite high and it is not rare to have multiple minor-stoppages occurring simultaneously. Since one operator deals with several machines, a machine with a minor-stoppage may have to wait until it is attended by the operator. Because of such waiting times, the machine downtimes due to minor-stoppages often exceed 40% of the working hours of a day. Accordingly, it is extremely important to develop effective ways for controlling such minor-stoppages.

In the literature, the issue of enhancing the yield and reducing the machine downtime in manufacturing has been addressed largely from the point of view of detecting root-causes of the product defects based on some data mining techniques. (Gardner and Bieker, 2000), for example, employ a combination of self-organizing map neural networks and rule induction to identify the critical poor yield factors in the wafer manufacturing process. In (Chen et al., 2005), correlations between combinations of machines and the defective products are first analyzed. The technique of association rule mining is then used to establish the root-cause machine identifier efficiently. (Chien et al., 2007) focus on the wafer fabrication process and chal-

Arima S., Sumita U. and Yoshii J..
DEVELOPMENT OF SEQUENTIAL ASSOCIATION RULES FOR PREVENTING MINOR-STOPPAGES IN SEMI-CONDUCTOR MANUFACTURING.
DOI: 10.5220/0003713503490354
In *Proceedings of the 1st International Conference on Operations Research and Enterprise Systems* (ICORES-2012), pages 349-354
ISBN: 978-989-8425-97-3

lenge the problem of detecting root-causes based on a Kruscal-Wallis test, K means clustering and the variance reduction approach.

While these contributions may enable one to identify the correlation structure between combinations of machines and the defective products, and detect root-causes of the defections, they do not provide preventive maintenance policies automatically. In particular, in semi-conductor manufacturing, effective methodological tools for preventing the minor-stoppages are hard to come by. Part of the reason for this difficulty may be found in that there are many different potential sources of minor-stoppages. Certain minor-stoppages may be attributed to factors related to products, including shape, size, weight, pins, and the like. Deterioration of machine conditions may cause minor-stoppages. HR (Human Resource) related factors such as work-shifts, skills of workers and training programs would also affect minor-stoppages.

The purpose of this paper is to establish effective preventive maintenance policies for controlling minor-stoppages in semi-conductor manufacturing. Our approach is to first classify types of minor-stoppages based on real data. These types are categorized in such a way that, once a type of a minor-stoppage is identified, the cause of the minor-stoppage could be located with high probability. The next step is to analyze a sequence of minor-stoppages by types where occurrences of certain minor-stoppages would be recognized to trigger minor-stoppages of other type, thereby providing a foundation for establishing preventive maintenance policies. This kind of the association rule approach is prevalent in marketing and is often employed for discovering purchasing patterns to be expected with high probability. The uniqueness of this paper is to develop such association rules based on sequential data along the time axis so that the resulting rules could be used for predicting occurrences of certain minor-stoppages.

The structure of this paper is as follows. The testing process in SAW (Surface Acoustic Wave) manufacturing is described in a succinct manner in Section 2. Along with the testing process, 10 minor-stoppages of principal interest are explained in detail. Section 3 is devoted to establish the association rules for predicting occurrences of such minor-stoppages. Numerical results are provided in Section 4 based on real data, demonstrating the practical usefulness of the proposed approach. Some concluding remarks are given in Section 5.

Throughout the paper, vectors are indicated by underbars, e.g. $\underline{a}^T = [a_1, \ldots, a_N]$, etc.

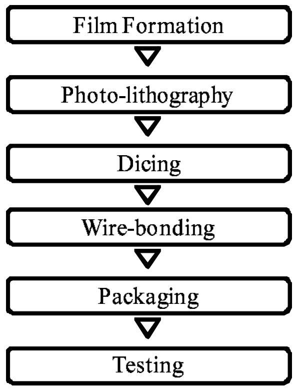

Figure 1: Six major stages of SAW manufacturing processes.

2 SAW MANUFACTURING PROCESS

We consider the manufacturing process of SAW filters, which are used in mobile phones, optical routers and the like for screening out electronic signals outside a pre-specified frequency range so that electronic noises can be eliminated in communication. The manufacturing process consists of six production stages as depicted in Figure 1.

The first stage is to cover the surface of each silicon wafer with a thin film through chemical vapor deposition, followed by photo-lithography to create a circuit pattern within the silicon wafer. These two stages are repeated so as to form a layer of circuit patterns. Then individual silicon wafers are cut into chips through dicing. In wire-bonding and packaging, each chip is mounted onto a metallic lead-frame and is covered by a cap. All of the finished products then go through complete testing before shipment to customers. In this paper, we focus on the testing stage and establish preventive maintenance policies for controlling minor-stoppages within the testing procedure.

The structure of a testing machine is depicted in Figure 2 for facilitating the explanation of the detailed operations involved in the testing procedure. Here, sensors A through N are indicated by putting each of them in a square. In line with the convention, throughout the paper, we call a finished product "a work". Several thousands of works constituting a lot are first placed into the bowl-feeder, which rotates counter clockwise so as to feed works into the linear-feeder. Sensors A and B located near the entrance to the linear-feeder examine whether or not the right face of a work is placed up. If Sensor A detects a work with face down, it turns on the system to flip the work over by blowing air. If the work is still judged

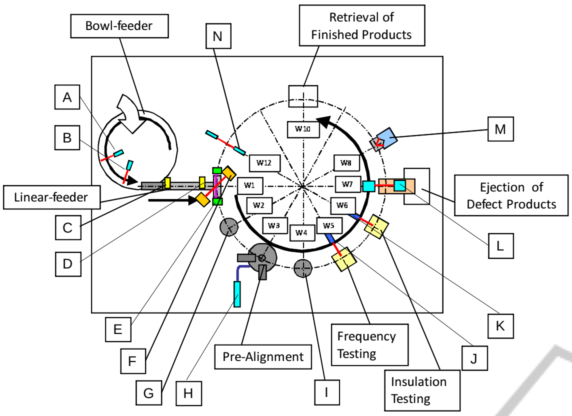

Figure 2: Structure of a testing machine.

as its face down by Sensor B, it would be blown back to the bowl-feeder by ejecting air.

At the entrance of the linear-feeder, Sensor C determines whether or not a work is there. The first work fed into the linear-feeder would turn on the vibration system which facilitates all the works within the linear-feeder to be moved forward toward the entrance to the wheel mechanism. Since the wheel mechanism rotates around 12 fixed stations located in equal angular positions with fixed time interval, we name the 12 stations Wi, i=1, 2, c , 12 in sequence counter clockwise. Upon reaching W1, a work is sucked into one of the 12 heads of the wheel mechanism to be moved counter clockwise to W2, W3, etc.

There are two types of minor-stoppages possible in the feeding process. The first case is that the bowl-feeder is stuck and the linear-feeder is starved. The second case is due to completion of the entire lot of works, which requires a new lot of works to be fed into the bowl-feeder. The former is called “PF-Stuck Al” where PF stands for Parts Feeder and Al means Alarm, while the latter is named as “WC Al” with WC describing Work Completion. In order to cope with PF-Stuck Al and WC Al, Sensors D, E and F are employed as shown in Figure 3. Sensor D is located at the point of the ten work length from W1. Sensor E is attached to the stage of W1, and Sensor F is installed at the up position of a head of the wheel mechanism above W1. PF-Stuck Al is detected if Sensor F signals no work present 10 times in a row under the condition of either “Sensor D identifying the presence of a work and Sensor E signaling non-existence of a work” or “Sensor E recognizing the presence of a work”. WC Al is detected if either “Sensors E and F signal non-existence of a work simultaneously 10 times in a row” or “Sensor F signals non-existence of a work 15 times in a row”. Sensor F would also see if the work is sucked in an appropriate position. If not, “WS-F Al” is detected where WS-F stands for Work Supply-

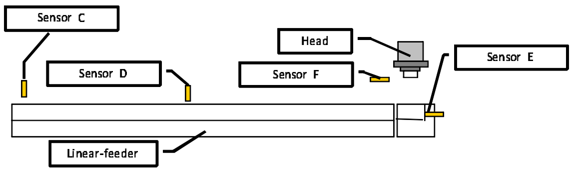

Figure 3: Locations of sensors along the linear-feeder.

Failure. Upon detecting PF-Stuck Al, WC Al or WS-F Al, the testing machine is automatically stopped and the appropriate alarm is signaled. This alarming process is similar for other minor-stoppages and will not be mentioned hereafter.

Upon reaching W2, a work remains to be sucked to the head and Sensor G of W2 checks if the work is there and the bottom of the work shows the correct side. If the bottom side is correct, R-at-W2-Flag is set to be 1 where R stands for Recognizable. In this case, it is also checked to see if the horizontal position of the work is appropriate, finding the corrective rotational angle to be implemented at W3, if necessary. If the bottom side is found to be wrong, R-at-W2-Flag is set to be 0. At W3, as soon as a work is placed back to the stage with the corrective rotation if necessary, a vacuum sensor called Sensor H is activated. If the work was not sucked appropriately to the head previously and was not corrected at W3, it would not cover Sensor H completely, resulting in air leak. In this case, “PASM Al” is signaled, where PASM means Pre-Alignment Sucking Miss. At W4, Sensor I similar to Sensor G is switched on. If the two sensors do not produce consistent judgment concerning the presence of a work, PASM Al is also reported. When the work is placed 180in a wrong direction, the above air leak test may still be passed. If Sensor I detects this case, R-at-W4-Flag is set to be 0. Otherwise, it is set to be 1.

At W5, each work is tested to see if its frequency falls into the pre-specified range. If the test is successful, F-Flag is set to be 1 with F meaning Frequency. Otherwise, it is set to be 0. Upon completion of the test, Sensor J is turned on to make sure that the work is moved to W6. If Sensor J detects the work left on the stage of W5, “WL-at-W5 Al” is issued where WL-at-W5 stands for Work Left at W5. W6 is to check if the insulation functions properly. Upon completion of the insulation test, I-Flag is set to be 1 if successful, and 0 otherwise, where I stands for Insulation. As for Sensor J at W5, Sensor K at W6 is then set on to see whether or not the work is transferred to W7 appropriately. If not, “WL-at-W6 Al” is reported.

Sensor L is activated at W7 to see if there is a work on the stage of W7. If it reports non-existence of a work despite Sensor F reported otherwise, “SM Al” is issued where SM stands for Sucking Miss. If any of

R-at-W2-Flag, R-at-W4-Flag, F-Flag and I-Flag has the value of 0, the work is detected as a defect at W7. Such defects are sorted according to the values of the flags and are dropped into appropriate cells. Sensor M checks the presence of a work at W8. If it finds a work, the values of R-at-W2-Flag, R-at-W4-Flag, F-Flag and I-Flag for the work are examined. If any of them is 0, it means that the work is failed to be detected as a defect at W7 and "FDD Al" is issued where FDD means Failure to Detect a Defect. After W8, each work is passed over to W9 without doing anything and reaches W10 where it is pushed out into a tray as a finished product. Necessary statistics are also collected at W10 to see if the cumulative yield of finished products stays above a pre-specified level. If this level is not met, "YF Al" is reported with YF meaning Yield of Finished products.

The wheel mechanism continues to rotate over W11 and Sensor N at W12 examines to make sure that there is no work present at W12. If any, it implies that a finished product was not taken out appropriately at W10 and "FRF Al" is issued where FRF stands for Failure to Retrieve a Finished product. The definitions of the flags are provided in Table 1. The ten minor-stoppages of principal interest to this paper discussed above are summarized in Table 2.

Table 1: The definitions of the flags.

Name		Position	Sensor
R-at-W2-Flag	Recognizable at W2	W2	G
R-at-W4-Flag	Recognizable at W4	W4	I
F-Flag	Frequency	W5	-
I-Flag	Insulation	W6	-

Table 2: The ten minor-stoppages.

Name		Position	Sensor
PF-Stuck Al	Parts Feeder Stuck	Linear-feeder	D,E,F
WC Al	Work Completion	Linear-feeder	E,F
WS-F Al	Work Supply Failure	W1	F
PASM Al	Pre-Alignment Sucking Miss	W3,W4	G,H,I
WL-at-W5 Al	Work Left at W5	W5	J
WL-at-W6 Al	Work Left at W6	W6	K
SM Al	Sucking Miss	W7	F,L
FDD Al	Failure to Detect a Defect	W8	M
YF Al	Yield of Finished product	W10	-
FRF Al	Failure to Retrieve a Finished product	W12	N

3 DEVELOPMENT OF ASSOCIATION RULES FOR PREVENTING MINOR-STOPPAGES BASED ON SEQUENTIAL DATA

For analytical purposes, we define a "window" as a set of works constituting a production lot, typically with its size in the range from 5000 to 60000 and its average around 30000. All orders under consideration are then expressed as a sequence of windows of length K along the time axis for each testing machine. The purpose of this section is to develop association rules, each of which indicates that the occurrence of a certain combination of minor-stoppages in a certain pattern within 2 consecutive windows would be likely to result in the occurrence of specific minor-stoppages in the immediately following window.

The problem of how to mine association rules from a large-scale data set has been addressed by many researchers, represented by (Agrawal et al., 1993) and (Agrawal and Srikant, 1994). Subsequently, the association rule approach has been applied to sequential data for prediction, see e.g. (Agrawal and Srikant, 1995), (Lu et al., 1998), (Jiang and Gruenwald, 2006) and (Qin and Shi, 2006) to name a few. However, these papers are exclusively dealing with marketing problems. To the best knowledge of the authors, the sequential association rule approach has not been applied to production control.

Real data have been collected from a semiconductor factory producing SAW devices. The data set consisting of K_L windows would be used as the learning data and a set of association rules would be established tentatively by following the procedure described in this section. The next K_T windows would be then used as the testing data, where a tentative association rule is chosen to be a formal rule if the accuracy of the association rule over the testing data exceeds a pre-specified level. For each of such formal rules, an action plan is devised so as to reduce the minor-stoppages.

In practice, the learning data may be collected for 3 months, while the testing data may consist of the windows over the subsequent 2 months. The resulting selected association rules would be applied to real data for 1 month following the testing period so as to reduce minor-stoppages. This learning-testing procedure would be repeated monthly on a rolling horizon basis for updating the selected association rules.

Let $\mathcal{N} = \{1,\ldots,N\}$ be the set of types of minor-stoppages under consideration, and define the minor-stoppage occurrence vector $\underline{x}^T(k) = [x(k,1),\ldots,x(k,i),\ldots,x(k,N)]$, where $x(k,i)$ denotes the number of minor-stoppages of type i occurred in the k-th window. We intend to establish association rules by observing the incremental changes

$$\Delta\underline{x}^T(k) = \underline{x}^T(k) - \underline{x}^T(k-1),\ k = 2,\ldots,K_L, \quad (1)$$

in relative to its mean and variance over the entire K_L

windows. More formally, let $\underline{\mu}$ and $\underline{\sigma}^2$ be defined by

$$\begin{aligned} \underline{\mu} &= [\mu_1, \ldots, \mu_N] \ ; \\ \mu_i &= \frac{1}{K_L - 1} \sum_{k=2}^{K_L} \Delta x^T(k,i) \ , \end{aligned} \tag{2}$$

and

$$\begin{aligned} \underline{\sigma}^2 &= [\sigma_1^2, \ldots, \sigma_N^2] \ ; \\ \sigma_i^2 &= \frac{1}{K_L - 2} \sum_{k=2}^{K_L} \{\Delta x(k,i) - \mu_i\}^2 \ . \end{aligned} \tag{3}$$

Then $\Delta x(k,i)$ can be standardized as

$$\begin{aligned} \underline{z}(k) &= [z(k,1), \ldots, z(k,N)] \ ; \\ z(k,i) &= \frac{\Delta x(k,i) - \mu_i}{\sigma_i} \ . \end{aligned} \tag{4}$$

Based on the value of $z(k,i)$, we introduce the indicator function $I(k,i)$ for describing whether the i-th minor-stoppage in the k-th window is in tendency of decreasing, being stable, or increasing. Namely, for a given threshold value $\alpha > 0$, we define

$$I(k,i) = \begin{cases} -1 & if \ \ z(k,i) \leq -\alpha \\ 0 & if \ \ z(k,i) \in (-\alpha, \alpha) \\ 1 & if \ \ z(k,i) \geq \alpha \end{cases} . \tag{5}$$

If $z(k,i)$ exceeds α, the i-th minor-stoppage is judged to be in increase in the k-th window. If the value is within $\pm\alpha$, it is considered to be in a stable state. When the value falls below α, the i-th minor-stoppage is defined to be in decrease.

Let $M(k,i,y)$ be the number of occurrences of $y \in \{-1, 1\}$ for the i-th minor-stoppage in the $(k-1)$-st and the k-th windows. If we define $\delta_{\{ST\}} = 1$ if the statement ST is true and $\delta_{\{ST\}} = 0$ otherwise, $M(k,i,y)$ can be written from (5) as

$$M(k,i,y) = \delta_{\{I(k-1,i)=y\}} + \delta_{\{I(k,i)=y\}} \ . \tag{6}$$

A typical association rule $\mathcal{R}$ would consist of the condition part expressed in terms of a set of $M(k,i,y)$'s for $i \in \mathcal{N}$ and $y \in \{-1, 1\}$, and the conclusion part written as $I(k+1, r) = 1$ for some $r \in \mathcal{N}$.

In order to identify such association rules from the learning data, the traditional measures of SUPPort, CONFidence and LIFT are employed. For notational convenience, a "unit" is defined as a set of three consecutive windows for which an association rule can be tested. We note that, for the learning data consisting of K_L windows, there are $K_L - 3$ units since $\Delta \underline{x}^T(k)$ in (1) can be defined only for $k \geq 2$ and the last two windows would not have the third window for testing the conclusion part of an association rule.

Given an association rule $\mathcal{R}$, let $VAL(\mathcal{R})$ be the set of units for which $\mathcal{R}$ is VALid. Similarly, we define $COND(\mathcal{R})$ and $CONC(\mathcal{R})$ to be the set of units meeting the CONDition of $\mathcal{R}$ and that satisfying the CONClusion of $\mathcal{R}$ respectively. It should be noted that $VAL(\mathcal{R}) = COND(\mathcal{R}) \cap CONC(\mathcal{R})$. The three measures $SUPP$, $CONF$ and $LIFT$ are then defined as

$$SUPP(\mathcal{R}) = \frac{|VAL(\mathcal{R})|}{K_L - 3} \ , \tag{7}$$

$$CONF(\mathcal{R}) = \frac{|VAL(\mathcal{R})|}{|COND(\mathcal{R})|} \tag{8}$$

and

$$LIFT(\mathcal{R}) = \frac{|CONF(\mathcal{R})|}{|CONC(\mathcal{R})| / (K_L - 3)} \ , \tag{9}$$

where $|A|$ denotes the cardinality of a set A. One observes that, $SUPP(\mathcal{R})$ is the portion of the units satisfying $\mathcal{R}$ against the entire $K_L - 3$ units, while $CONF(\mathcal{R})$ is that against the set of the units satisfying the condition part of $\mathcal{R}$. $LIFT(\mathcal{R})$ describes how the probability of selecting a unit satisfying the conclusion part of $\mathcal{R}$ from the entire $K_L - 3$ units can be lifted by restricting the sample set to the units meeting the condition part of $\mathcal{R}$.

Given $\alpha > 0$ in (5) along with $\beta > 0$ and $\gamma > 0$, we define the followings.

a) An association rule $\mathcal{R}$ is said to be effective on data $\mathcal{D}$ if $SUPP(\mathcal{R}) \geq \beta$, $CONF(\mathcal{R}) \geq \gamma$ and $LIFT(\mathcal{R}) > 1$.

b) An association rule $\mathcal{R}$ is said to be formal if it is effective on both the learning data and the testing data.

For each of the selected formal rules, an action plan is devised so as to reduce the minor-stoppages by implementing the action plan whenever the condition(s) of the rule could be observed.

4 NUMERICAL RESULTS

In this section, we present numerical results based on real data obtained from a semi-conductor manufacturing plant, where one testing machine was observed for minor-stoppages continuously. The data collected through the three month period January-March 2010 constitute the learning data with $K_L = 166$, while the following two month data in April and May would be used for testing with $K_T = 84$. The ten types of minor-stoppages discussed in Section II are considered for analysis, where

$$\begin{aligned} \mathcal{N} = \{ & \text{PF-Stuck}, \text{WC}, \text{WS-F}, \text{PASM}, \text{WL-at-W5}, \\ & \text{WL-at-W6}, \text{SM}, \text{FDD}, \text{YF}, \text{FRF}\} \ . \end{aligned} \tag{10}$$

With $\alpha = 0.5$, $\beta = 0.02$ and $\gamma = 0.30$, forty-four rules are found to be effective based on the learning data. By examining these rules against the test data, five rules are selected to be formal, as shown in Table 3. For each of the five rules, Table 4 exhibits the three indices $SUPP$, $CONF$ and $LIFT$ based on the learning data as well as the test data.

Table 3: Effective association rules.

No	LHS		RHS
1	$M(k,\text{WC},1) = 1$	$\Rightarrow$	$I(k+1,\text{WS-F}) = 1$
2	$M(k,\text{FRF},1) = 1$ $M(k,\text{FRF},-1) = 1$	$\Rightarrow$	$I(k+1,\text{WS-F}) = 1$
3	$M(k,\text{FRF},1) = 1$ $M(k,\text{FRF},-1) = 1$	$\Rightarrow$	$I(k+1,\text{PF-Stuck}) = 1$
4	$M(k,\text{WC},-1) = 1$ $M(k,\text{WS-F},-1) = 1$	$\Rightarrow$	$I(k+1,\text{WS-F}) = 1$
5	$M(k,\text{WL-at-W6},1) = 1$ $M(k,\text{PF-Stuck},-1) = 1$	$\Rightarrow$	$I(k+1,\text{PF-Stuck}) = 1$

Table 4: $SUPP$, $CONF$ and $LIFT$ for rules 1 through 5.

No	Data	*SUPP*	*CONF*	*LIFT*
1	Learning	0.066	0.306	1.691
	Test	0.060	0.313	1.382
2	Learning	0.030	0.385	2.128
	Test	0.048	0.364	1.608
3	Learning	0.024	0.308	1.502
	Test	0.048	0.364	2.036
4	Learning	0.030	0.333	1.844
	Test	0.036	0.333	1.474
5	Learning	0.030	0.500	2.441
	Test	0.024	0.667	3.733

The conclusion parts of the five rules consist of the increase of WS-F or PF-Stuck. In order to prevent WS-F, it would be effective to clean the head parts of the wheel mechanism, while cleaning the linear-feeder would decrease the likelihood of occurring PF-Stuck. Hence, the preventive maintenance policies derived from the five rules would be :

1) if the condition part of Rule 1, Rule 2 or Rule 4 is realized, then clean the head parts of the wheel mechanism; and

2) if the condition part of Rule 3 or Rule 5 is realized, then clean the linear-feeder.

5 CONCLUSIONS

In this paper, a novel approach is proposed for establishing preventive maintenance policies so as to control the minor-stoppages in the testing process of semi-conductor manufacturing. Based on the real data collected from an actual factory, sequential association rules are established, where the occurrence of a certain combination of minor-stoppages within two consecutive windows would indicate the likelihood of occurrence of a certain minor-stoppage to become higher in the next window. Five association rules are found to be effective, yielding two preventive maintenance policies in a concrete form. While the paper focuses on the testing process, the methodology proposed in this paper is valid for other production processes, provided that similar sequential data could be collected.

REFERENCES

Agrawal, R., Imielinski, T., and Swami, A. (1993). Mining association rules between sets of items in large databases. *Proceedings of the 1993 ACM SIGMOD International Conference on Management of Data*, pages 207–216.

Agrawal, R. and Srikant, R. (1994). Fast algoritms for mining association rules. *Proceedings of the 20th Conference on Very Large Data Bases*, pages 478–499.

Agrawal, R. and Srikant, R. (1995). Mining sequential patterns. *Proceedings of the International Conference on Data Engineering*.

Chen, W., Tseng, S., and Wang, C. (2005). A novel manufacturing defect detection method using association rule mining techniques. *Expert Systems with Applications*, 29:807–815.

Chien, C., Wang, W., and Cheng, J. (2007). Data mining for yield enhancement in semiconductor manufacturing and an empirical study. *Expert Systems with Applications*, 33:192–198.

Gardner, M. and Bieker, J. (2000). Data mining solves tough semiconductor manufacturing problems. *Proceedings of the sixth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*.

Jiang, N. and Gruenwald, L. (2006). Research issues in data stream association rule mining. *ACM SIGMOD Record*, 35(1):14–19.

Lu, H., Han, J., and Feng, L. (1998). Stock movement prediction and n-dimensional inter-transaction association rules. *Proceedings of the 1998 ACM SIGMOD Workshop on Research Issues on Data Mining and Knowledge Discovery*, pages 12:1–12:7.

Qin, L. and Shi, Z. (2006). Efficiently mining association rules from time series. *International Journal of Information Technology*, 12(4):30–38.