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Maximizing the Productivity of Photolithography Equipment by Machine Learning Based on Time Analytics

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Abstract: Maximizing productivity is one of the most critical factors for competitiveness in the manufacturing industry. Needless to say, the semiconductor industry, in which the automation rate is relatively high and the manufacturing process continues 24 h a day, requires high productivity to be maintained. This paper is about a model that analyzes the cause of an increase in time needed for the whole photolithography process and automatically classifies it in real-time by machine learning. The time analytics model based on a k-means algorithm divides the processing time into four hundred detailed time steps and classifies causes through normalizing and clustering processes. Further, true/false measures of performance were employed based on the confusion matrix. To increase the accuracy of the model, the classified cause becomes a source for creating a new algorithm that can detect problems quickly and accurately. A small number of wafers that the system has failed to classify has accumulated in the database to increase the frequency of occurrence. As a result of evaluating the time analytics model in the photolithography extreme ultraviolet (EUV) equipment, the model has classified 98.6% of the wafers that exceed the limitation. Continuous updates of new phenomena that will be generated from advanced technologies will be more important than the current classification ability. We are accumulating unclassified data for a sustainable system and will continue to classify by synthesizing new phenomena. Data classified in real-time with high accuracy become a steppingstone for maintaining high productivity. Production equipment and processes are developed to enhance individual characteristics. Nevertheless, a data mining method that divides the process time can also be widely used in manufacturing processes of other fields.

Keywords: time analytics; photolithography process; manufacturing; data mining; classification

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1. Introduction

The intensifying global competition has made it imperative for manufacturing companies to maximize their production volume. The overall equipment efficiency (OEE) proposed by Nakajima presented a standard for quantitatively measuring the performance of equipment, and numerous manufacturers have been using it to measure and improve productivity [1–3]. In particular, the number of manufacturers using OEE is increasing in large-scale automation for mass production [4–7]. Accurate performance data of equipment is the crucial factor for success in maximizing productivity by maintaining and improving manufacturing efficiency. OEE is a macroscopic method that measures how well equipment is theoretically running compared to its full potential in the real world [8]. Even though OEE is an effective way of measuring equipment efficiency, the biggest concern for manufacturers is to instantly detect and improve the causes of efficiency degradation to maintain maximum efficiency. Semiconductor production sites are attempting prediction, classification, association analysis, and clustering using data mining methods. However, the purpose of most of the research is to improve the quality of wafers based on the defect map of the wafers. Very few studies are related to productivity improvement [9–12].

Statistical process control (SPC) methods, and the widely used analytical methods therein, have been commonly used with fault detection and classification data. SPC refers to a statistical methodology that examines critical variables that must be placed within certain specifications. However, the SPC has the limitation that only a few of the manufacturing processes affected by hundreds of factors can be investigated and controlled. In addition, since the SPC does not have clear criteria for distinguishing fault detection and classification data, it may obtain results that are not related to factors, and it is impossible to analyze in real-time. In this work, we created a time analytics model that classifies the causes of efficiency degradation in real-time based on the ideal time required for each process and the data provided by the equipment in the actual industry. The process time is divided into approximately four hundred detailed steps, and the causes are classified through normalizing and clustering processes based on a k-means algorithm [13–16]. Further, true/false measures of performance were employed based on the confusion matrix. The existing equipment required one decade to analyze the cause of increased process time, but when applying the time analytics model, the cause of modern extreme ultraviolet (EUV) equipment, which is more complex than the existing equipment, up to 98.6% can be classified in real-time. Accurate and detailed classification of time will be the basis for continuously maintaining maximum efficiency by reducing the time and effort spent on detecting the cause of productivity degradation.

2. Related Works

2.1. Statistical Process Control

Statistical process control (SPC) methods are commonly used in the manufacturing industry [17]. A univariate SPC value is used to control an important single target value so that it is within a specific range (Figure 1a). In the case where the SPC value is out of the specific range (red dots), SPC reports a fault. SPC is generally a simple and effective system that controls key factors related to quality. Whereas the time analytics model is a simple and powerful system that not only controls process time but also checks the cause of productivity degradation immediately. Figure 1b shows the wafer loading time in the time analytics model. The control range is the normal distribution of the cluster closest to the minimum time. The lower control limit (LCL) is the minimum wafer loading time (blue dot) and the data only exceeding the upper control limit (UCL) are detected as a time-increased wafer. The EUV equipment repeats the process of exposing the reticle pattern to the wafer with the light source and loading the next wafer. The system categorizes the process time into three categories (expose time, loading time, and lot interval) by combining the time at the beginning and end of exposure and controlling each range (Figure 1c). This paper has focused on loading times that have relatively large variations and require improvement.

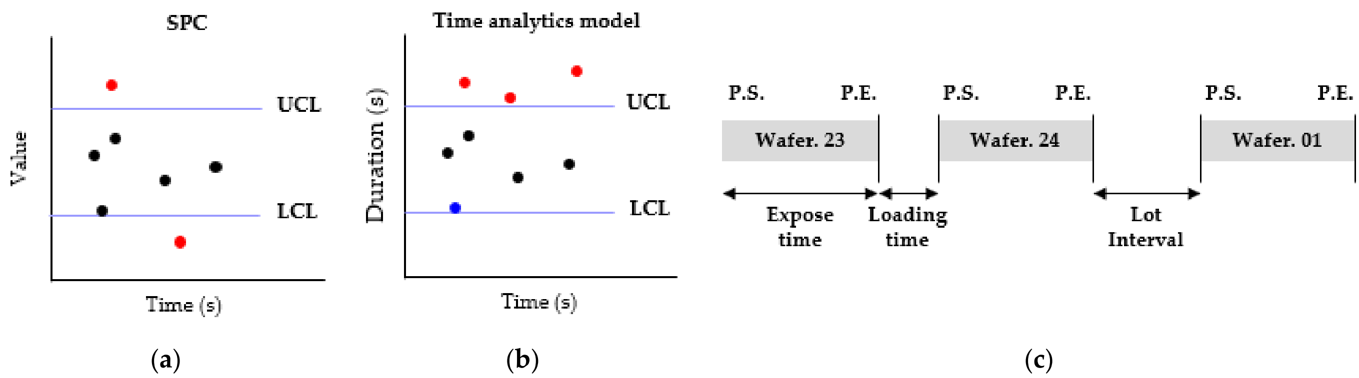

Figure 1. (**a**) Shows the general SPC trend. Red dots represent the outside of control range. (**b**) Shows the loading time of each wafer in the control chart. A blue dot is the maximum ability of the equipment, and it cannot be placed under LCL. (**c**) Shows the classification of process time. (P.S.: Process Start, P.E.: Process End).

2.2. Time Analysis of Two Equipment Makers

Two of the photolithography equipment makers have a time analysis system. The A company created logic that analyzes the increased value of process time based on the log generated by the equipment (Equation (1)). The equipment log, which is the information data of the equipment that comes out as the process progresses, has high accuracy and reliability. The C company expressed the process time as the length of the bar and the wafer loading time as the interval between the bars based on the signal that the equipment communicates with a server. The simple graphs and pictures have high visibility. Contrarily, equipment makers are not allowed access to the information of the process layer with numerous variables, which shows the limitations of the analysis. We employed the model for normalizing and clustering data based on the information of the process layer. Process layer information is an essential element for normalizing.

$$\text{The quantity of increased process time} = \text{Log A} - \text{Log B} - \text{Constant} \tag{1}$$

3. Time Analytics Model in Photolithography Equipment

3.1. Overview

The time analytics model classifies the cause of the increase in process time using two methods. First, cause classification uses a decision tree to classify time-increased wafers. The decision tree has the same number of algorithms as the number of types of classified causes. The simplest algorithm is made only with the same type of event code as AB-1234. The most used types of algorithms are made by combining equipment logs or sensor signals. Each algorithm is developed using the cross-industry standard process for data mining (CRISP-DM). Algorithms created by detailed equipment logs have high accuracy and currently classify 98.6% of time-increased wafers. Second, time classification classifies the 1.4% of the time-increased wafers that cannot be classified in cause classification by the machine learning method. Since there is no factor in classifying the cause, the process time (average 21.6 s) of the single wafer is divided into four hundred steps. Detailed time steps that affect the increase in the process time are detected through normalizing and clustering. After analyzing the characteristics of the classified clusters, a new algorithm is created and added to the decision tree. Figure 2 shows the flow of the time analytics system.

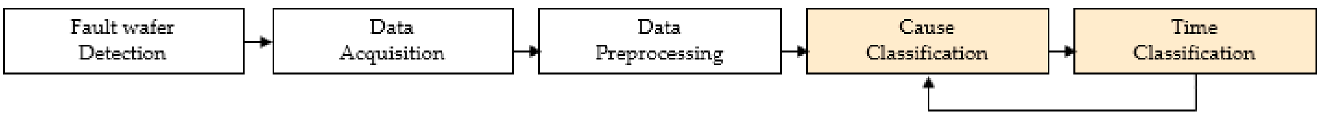

Figure 2. Time analytics model flow chart. Time classification is used to construct a new cause classification algorithm.

3.2. Typical and Atypical Time-Increased Wafers

We have defined the types of time-increased wafers outside the control range as two types: typical and atypical. Figure 3a shows the wafer loading time of each wafer in chronological sequence. Durations are clustering around 7 s (red dots). The same duration generally indicates the same cause. We have defined clustered time-increased wafers as a typical form. Contrarily, time-increased wafers that do not form clusters have been defined as an atypical form. The atypical form has characteristics of large dispersion and low frequency of occurrence. The ratio of atypical time-increased wafers is 9.1% of the total wafers, and some atypical time-increased wafers also have the same duration as typical time-increased wafers, resulting in a decrease in the accuracy of the classification. The study has assumed that external factors are likely to be atypical. The transport of materials (wafer and photomask) is one of the external factors. The photolithography process requires the transport of 4000 wafers and 100 photomasks per day. There is a possibility that supply will be delayed due to several reasons during transportation. As a result of analyzing ten signals related to wafer transport, it could be defined as a polynomial with three independent variables. Equation (2) shows the delay of the transporting wafer from the outside, and

Equation (3) shows the delay of transporting the wafer to the outside. The constants T_1 and T_2 are the minimum times of the difference between the two signal occurrence times of each equation. In cases when the interval between the occurrences of the two signals is greater than the minimum time (T_1, T_2), the transport delay of the wafer can be calculated. In addition, transportation delays could be classified by analyzing the transport signal of the photomask. Equation (4) shows the delay in receiving the photomask. As a result of the experiment, the time-increased wafer due to the delay in material supply, which is an external factor, had an atypical form, and by classifying it, the ratio of unclassified time-increased wafers could be lowered from 9.1% to 1.4%. The classification of material supply delays reduced 85% of atypical time-increased wafers and was able to increase the accuracy of typical data. In addition, by accumulating data on unclassified atypical time-increased wafers, it was possible to detect clusters with a low frequency of occurrence.

$$\text{Wafer receive delay} = (\text{Signal A} - \text{Signal B}) - T_1 \tag{2}$$

$$\text{Wafer give delay} = (\text{Signal } C_1 - \text{Signal} C_2) - T_2 \tag{3}$$

$$\text{Reticle receive delay} = (\text{Signal D} - \text{Signal E}) - T_3 \tag{4}$$

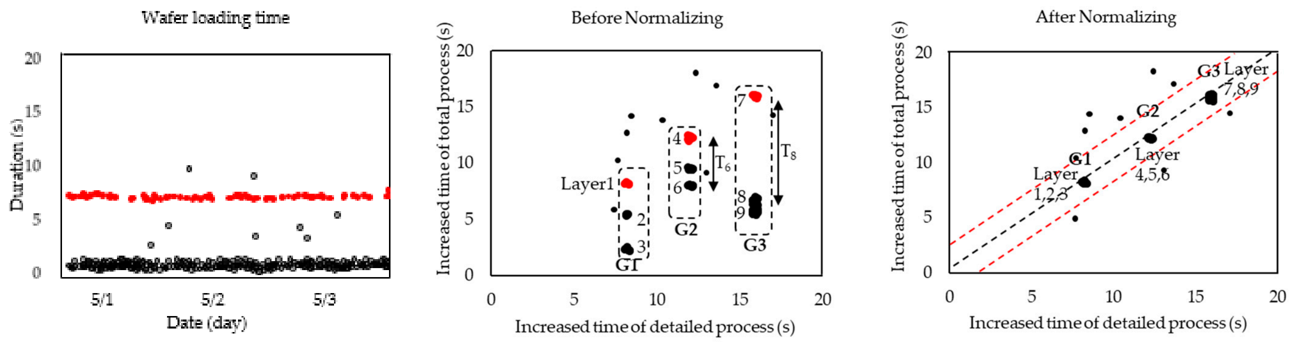

Figure 3. (**a**) Shows wafer loading time of each wafer, where red data are clustered in a specific time range. (**b**,**c**) Show the process of normalization, where each layer has different waiting times (T_i) for normalization.

3.3. Time Classification Based on Machine Learning

The cause classification classified the typical time-increased wafer (90.9%) and the material supply delay (7.7%). Unclassified time-increased wafers (1.4%) are characterized by not easily clustering due to the low frequency of occurrence. To increase the frequency of occurrence, we have expanded the data collection period and target equipment for the time-increased wafer. The collected time-increased wafers have been classified by generalizing and clustering. This classification method by machine learning was defined as time classification. Most algorithms of cause classification are created through time classification clustering. Hence, the order of the two-classification methods cannot be clearly figured out. Time classification has the following flow: In the photolithography EUV process, the process of a single wafer is divided into 400 detailed processes for 30 s. The average duration of the detailed process is 75 milliseconds. Figure 3b shows the max increased time (X_i) of the detailed process and the increased time (Y_i) of the total process. Groups G1, G2, and G3 have similar values of Xi and have the same process name tag. In contrast, the values of Y_i are generally different. Increased time of the total process has a large dispersion due to the characteristic of the equipment. EUV equipment has twin chucks. While the previous wafer exposes the pattern on one chuck, the next wafer performs measurements on the other chuck, which is the previous step of exposure. Most wafers have a longer exposure time than measurement time. Hence, it has a waiting time after measurement and has different correction factors (T_i) due to the different process times of each layer. Normalizing is an essential step for clustering as a method to remove the characteristics of the process layer (Equation (5)). Figure 3c shows the results of the normalization of nine layers. Normalized data are clustered by the k-means algorithm, which is one of the clustering methods.

$$F(X_i, T_i) = \alpha\,(X_i + T_i) \tag{5}$$

$$\text{precision} = \frac{TP}{TP + FP},\ \text{recall} = \frac{TP}{TP + FN},\ \text{accuracy} = \frac{TP + TN}{TP + FN + FP + TN} \tag{6}$$

4. Results

The time analytics system has various types of input data. The event log of the equipment, one of the most commonly used data, provides accurate information and detailed time and provides approximately 200 pieces of information per wafer. Hence, the performance of the model was evaluated as a wafer transport delay classification with relatively little accuracy. Sensor signals only provide second-by-second resolution and on/off data. Performance was evaluated via three items (precision, recall, and accuracy) based on the confusion matrix (Equation (6)) (Table 1). Classification evaluation metrics using precision, recall, and accuracy are used to measure the performance of the classification by the machine learning model [18,19]. The ratio of time-increased wafers is approximately 12% of the total wafers, and the ratio of time-increased wafers due to transportation delay is less than 1%. Since the number of targets is extremely small, we have limited the evaluation target to time-increased wafers. The trueness/falseness was determined by analyzing the equipment on the other side of the wafer transportation. The cross-validation test was performed with the 5-fold dataset. Table 2 shows the results of the experiment. The result showed more than 90% precision, 96% recall, and 99% accuracy. Fold 4 has a higher number of false positives and a lower precision than other folds. As a result of equipment analysis, we have confirmed that the sensor signal of this equipment is delayed.

Table 1. True positive (TP), false positive (FP), false negative (FN), and true negative (TN) are defined based on the confusion matrix.

		Actual	
		True	**False**
Predict	True	TP	FP
	False	FN	TN

Table 2. Cross-validation test result.

	Wafers	TP	FP	FN	TN	Precision (%)	Recall (%)	Accuracy (%)
Fold 1	5120	452	22	11	4635	95.36	97.62	99.36
Fold 2	5034	320	18	9	4687	94.67	97.26	99.46
Fold 3	4825	351	12	8	4454	96.69	97.77	99.59
Fold 4	5244	414	42	10	4778	90.79	97.64	99.01
Fold 5	4151	337	16	13	3785	95.47	96.29	99.30

To verify the performance of cause classification, we have applied the system for three months to six EUVs currently being mass-produced. Table 3 shows the ratio of time-increased wafers for each piece of equipment and the classification ratio of each classification model. The proportion of time-increased wafers in the total wafers has been classified from 7.4% to 23.5%, and the cause classification has been classified at an average of 98.6%. Table 4 shows the number of occurrences for each cause classified by cause classification. The distribution of classification provides a lot of information to engineers. First, cause 7 has a high number of occurrences in all equipment. It shows the possibility that it is a structural issue or an essential process. Second, most causes are equipment dependent. Each cause has a large number of occurrences in a specific piece of equipment. The distribution of causes shows both problems and solutions for each piece of equipment. Finally, the time analytics model not only defines the number of occurrences and the amount of time delay by cause in real-time, but also suggests the solution and amount of productivity improvement.

Table 3. Ratio of time-increased wafers in total wafers and ratio of cause and time classification.

	Equipment. 1	Equipment. 2	Equipment. 3	Equipment. 4	Equipment. 5	Equipment. 6
Time-increased wafer (%)	23.50	9.94	8.30	17.45	7.85	7.39
Cause classification ratio (%)	98.65	97.89	98.16	98.72	99.32	99.07
Time classification ratio (%)	1.35	2.11	1.84	1.28	0.68	0.93

Table 4. Cause classification result shows the frequency of occurrence by each cause.

	Equipment. 1	Equipment. 2	Equipment. 3	Equipment. 4	Equipment. 5	Equipment. 6
Cause 1	3738	445	0	0	1	68
Cause 2	42	21	307	67	95	113
Cause 3	2029	1475	652	435	1113	824
Cause 4	53	20	87	477	18	20
Cause 5	771	1354	817	2744	785	756
Cause 6	7853	1697	150	3433	2	0
Cause 7	4989	6925	6507	6238	7856	7891
Cause 8	94	384	9	13	2546	2
Cause 9	116	117	123	633	77	35
Cause 10	245	79	2297	3878	43	231
Cause 11	184	743	24	3902	6	2175
Cause 12	0	13	1	0	0	1
Unclassified	276	286	206	282	86	114

Time-increased wafers (1.4%) that are not classified by the cause classification are classified by time classification. Time classification classifies time-increased wafers through normalizing and clustering processes. We found a system defect in the normalizing process during the experiment. Figure 4a shows an example of clustering without a normalizing process. The CT unstable DTRA, one of the causes, has been clustered after the target equipment and data collection period was extended because the occurrence rate was only 0.09%. Since it belongs to the wafer loading time, it was required to be normalized. Nevertheless, clustering was completed without normalizing. We have been able to find the solution in the definition of the wafer loading time (Equation (7)). To analyze all the time of the equipment, the system defined the time between the wafer exposure as the wafer loading time. Contrarily, there are other detailed processes between wafer loading and exposure start. The detailed processes after the actual wafer loading are not affected by the waiting time and do not require normalizing. Hence, the normalizing method has been modified. Figure 4b,c are examples of a cause that required normalizing and could classify clusters only after normalizing was completed. Three layers have similar max increased time of the detailed process (X_i) and a different increased time of total process (Y_i). The normalizing process of correcting the waiting time (T_i) for each layer is essential in mass production. In the case of SOSI_fallback, the probability of occurrence is only 0.9%. In addition, approximately thirty process layers have different waiting times (T_i) in mass production. Hence, the system recognizes the probability of occurrence of the cause as 0.03% and cannot complete clustering. We have been able to generalize more data by correcting the waiting time (T_i), which is characteristic of the equipment and process layer. In the future, the classification ratio of time-increased wafers is expected to be higher than the current 98.6%.

$$\begin{aligned} Wafer\ loading\ \ time \\ &= previous\ wafer\ exposure\ end \\ &- next\ wafer\ exposure\ start \end{aligned} \tag{7}$$

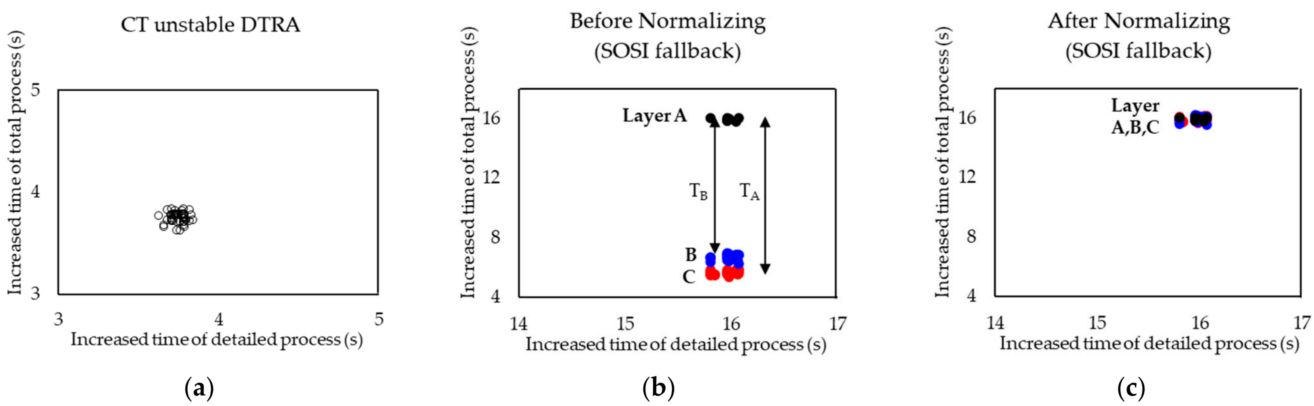

Figure 4. (**a**) Shows clustering without normalization, and (**b**,**c**) show before and after normalization of SOSI fallback, which is a specific process.

5. Conclusions

The time analytics model analyzes the increase in process time and classifies the increased causes through normalizing and clustering based on a k-means algorithm. Classified clusters are made into a more accurate algorithm through analysis. Based on the model, we classified the current increase in process time of EUV equipment as 98.6%. In addition, we introduced a process to obtain correlations of unclassified data with large dispersion using the algorithm and true/false as measures of performance based on the confusion matrix. A normalization method that compensates for the waiting time by accounting for the equipment structure and process layer characteristics has made it possible to classify the various causes of the wafer loading time. This paper focuses on providing an accurate and detailed classification of the time analytics model in real-time. In addition, the ultimate goal is to continuously increase and maintain the efficiency of semiconductor manufacturing through the system. Furthermore, research on new types of normalizing or clustering methods will enhance the model and increase the probability of classification. The time analytics model is an effective and sustainable model that combines knowledge technology and machine learning methods, and the simplicity of classifying time will not be an obstacle to using it in other types of processes and industries.

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