Photolithography Control in Wafer Fabrication Based on Process Capability Indices With Multiple Characteristics

W. L. Pearn, H. Y. Kang, A. H.-I. Lee*, and M. Y. Liao

Abstract—**Photolithography, typically taking about one- third of the total wafer manufacturing costs, is one of the most complex operations and is the most critical process in semiconductor manufacturing. Three most important parameters that determine the final performance of devices are critical dimension (CD), alignment accuracy and photoresist (PR) thickness. Process yield, a common criterion used in the manufacturing industry for measuring process performance, can be applied to examine the photolithography process. In this paper, we solve the photolithography production control problem based on the yield index S_{PK}. The critical values required for the hypothesis testing, using the standard simulation technique, for various commonly used performance requirements, are obtained. Extensive simulation results are provided and analyzed. The investigation is useful to the practitioners for making reliable decisions in either testing process performance or examining quality of an engineering lot in photolithography.**

Index Terms—**Alignment accuracy, critical dimension, critical value, photolithography, photoresist thickness, process yield.**

I. Introduction

THE MANUFACTURING of integrated circuits (ICs) with smaller devices and feature sizes on wafers of larger diameters has been a trend in the semiconductor industry in order to achieve a smaller die size, lower electric power consumption, more rapid operating speed and reduced manufacturing cost. The function of photolithography, which has the highest impact on the development of semiconductor manufacturing, is to project circuit patterns onto a silicon wafer with high fidelity and repeatability. As wafer fabrication technology upgrades to a higher precision level, the width of IC diagram copied from photolithography activity becomes smaller, and the final chip products possess a faster processing capability and a lower electricity requirement. Photolithography is considered as the bottleneck in semiconductor manufacturing because of the following reasons: photolithography has the most important equipment; a wafer may go through the process up to fifty times for producing a complex IC; and the process results are crucial to the final functions of a product. As a result, the process control of photolithography workstation is essential.

In photolithography, the pattern printed on a wafer is not an exact replica of the mask pattern in practice, and the variations result largely from three reasons [1]. First, the fundamental diffraction of the projection optics is limited. Second, the mask pattern itself is not exactly the same as the design due to the limitations of the mask fabrication process. Third, there are random and systematic variations of the multitude of photolithographic process parameters, such as focus and exposure. The process materials, the equipment and the processing environment also face time-varying fluctuations that cannot be easily measured, and such variations cause disturbances on the photolithography process [2]. Therefore, it is important to implement manufacturing control, which strives to maintain output within prescribed lower and upper specification limits [3]. Two of the most troublesome control tasks are the measurement of the alignment between layers and the measurement of the dimensions of the smallest features [4]. The alignment determines the success of transferring the IC design pattern on the mask or reticle to the PR on the wafer surface [5]. The latter are called "critical-dimensions" (CDs) and a CD is defined as the linewidth of the PR line printed on a wafer and reflects whether the exposure and development are proper to produce geometries of the correct size [2]. In additional to the above two parameters, PR thickness is also very important since it determines the resolution and the resistance of the PR film, and a specific thickness, which is consistent from wafer to wafer and uniform across each wafer, is required. As a result, alignment accuracy (AA), CD and PR thickness (PT) are the three parameters that have the greatest impact on device performance and that should be controlled properly.

Process yield, the percentage of processed product unit passing the inspection, is a common and basic criterion used in the manufacturing industry as a numerical measure on the performance. For a product to pass the inspection, its product characteristic must fall within the manufacturing tolerance, and all passed product units are equally accepted by the producer. On the other hand, for a product that is rejected due to nonconformities, it may be scrapped, or additional cost is required to repair the product. To examine the quality of wafers, the three key characteristics, AA, CD, and PR, should be examined. An index, S_{PK}^T, which provides an exact measure of the overall process yield is performed to assess process capability for the photolithography process. The rest of the paper is organized as follows. Section II presents the

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approach for photolithography production yield measurement. Section III calculates the photolithography production yield. Some conclusion remarks are made in the last section.

II. PCI Approach for Photolithography Production Yield Control

In this study, we investigate the photolithography process of a semiconductor fab in the Science-Based Industrial Park in Taiwan. The objective is to examine the process performance and present critical values for determining whether the process meets the capability requirement. In a wafer fab, each lot contains 25 pieces of wafers, and each piece of wafer has 400 chips. As a result, one lot has 10 000 chips. The number of chips, selected for CD, AA, and PT measurements, in a lot needs to be estimated. The manufacturing specifications for the three parameters are as follows:

$$\begin{aligned}&\mathrm{CD}: USL = 0.21\ \mathrm{um}, \quad \text{and} \quad LSL = 0.19\ \mathrm{um}.\\&\mathrm{AA}: USL = +10\ \mathrm{nm}, \quad \text{and} \quad LSL = -10\ \mathrm{nm}.\\&\mathrm{PT}: USL = 9100\ \text{Å}, \quad \text{and} \quad LSL = 8900\ \text{Å}\end{aligned}$$

where USL is the upper specification limit, and LSL is the lower specification limit.

Based on historical data, the process characteristics we investigated are justified to be in statistically control and runs in stable condition, which follows rather close to a normal distribution. In addition, there is no correlation among the three parameters. AA is totally independent with CD and PT since the AA measurement is to make sure that the reticles for different layers in photolithography process are aligned correctly and that the physical construction of each chip is consistent with the original design in consequence. As for the relation between CD and PT, it is determined by the characteristics of the chosen PR. For the chosen PR, swing curve, which shows the manufacturing range for the CD and PT, will be studied first for the manufacturing specifications. Within the range, CD and PT can be chosen independently based on the need of design and process without any interference. Therefore, within the given manufacturing specifications, there is no correlation for these two parameters.

Process capability indices (PCIs) are very important for measuring how well the process meets specifications. Based on the expression of process yield, Boyles [6] considered a yield measurement index S_{PK},

$$S_{PK} = \frac{1}{3}\Phi^{-1}\left\{\frac{1}{2}\Phi\left(\frac{USL-\mu}{\sigma}\right) + \frac{1}{2}\Phi\left(\frac{\mu-LSL}{\sigma}\right)\right\} \tag{1}$$

where μ is the process mean, σ is the process standard deviation, and $\Phi(\bullet)$ is the cumulative distribution function of the standard normal distribution N(0,1).

The index S_{PK} establishes the relationship between the manufacturing specifications and the actual process performance, and provides an exact measure of the process yield. The natural estimator $\hat{S}_{PK}$ can be applied to estimate the yield measurement index S_{PK} from a stable process [7]:

$$\hat{S}_{PK} = \frac{1}{3}\Phi^{-1}\left\{\frac{1}{2}\Phi\left(\frac{USL-\bar{X}}{s}\right) + \frac{1}{2}\Phi\left(\frac{\bar{X}-LSL}{s}\right)\right\} \tag{2}$$

TABLE I
The Corresponding Process Yield and NCPPM for Various Values S_{PK}^T

S_{PK}^T	Overall process yield (P)	NCPPM
1.00	0.9973002039	2700
1.25	0.9999158250	84
1.50	0.9999932047	6.8
1.75	0.9999999240	0.076
2.00	0.9999999980	0.002

TABLE II
S_{PK}^T Value for Three Characteristics

v	S_{PK}^T				
	1.00	1.25	1.50	1.75	2.00
3	1.20(0.2)2.00	1.40(0.15)2.00	1.60(0.1)2.00	1.80(0.1)2.20	2.10(0.1)2.50

where $\bar{X} = \Sigma_{i-1}^{n} X_i/n$ is the sample mean and the conventional estimator of μ, and $s = [\Sigma_{i-1}^{n}(X_i - \bar{X})^2/(n-1)]^{1/2}$ is the sample standard deviation and the conventional estimator of σ.

However, the exact distribution of $\hat{S}_{PK}$ is analytically intractable, and the process performance cannot be tested. The estimator can be expressed approximately by Taylor expansion as [8]:

$$\hat{S}_{PK} = S_{PK} + \frac{W}{6\sqrt{n}\phi(3S_{PK})} + \frac{O_P}{n} \tag{3}$$

$$\begin{aligned}W = {}& \frac{\sqrt{n}(S^2-\sigma^2)}{\sigma^2}\left\{\frac{d-(\mu-m)}{2\sigma}\phi\left(\frac{d-(\mu-m)}{\sigma}\right)\right.\\&\left.+\frac{d+(\mu-m)}{2\sigma}\phi\left(\frac{d+(\mu-m)}{\sigma}\right)\right\}\\&-\frac{\sqrt{n}(\bar{X}-\mu)}{\sigma}\left\{\phi\left(\frac{d-(\mu-m)}{\sigma}\right)\right.\\&\left.-\phi\left(\frac{d+(\mu-m)}{\sigma}\right)\right\}.\end{aligned} \tag{4}$$

Note that $W = (\sqrt{n/2})[a(S^2-\sigma^2)/\sigma^2] - \sqrt{n}\,[b(\bar{X}-\mu)/\sigma]$ for $\mu < m$, $W = (\sqrt{n/2})[a(S^2-\sigma^2)/\sigma^2] - \sqrt{n}\,[b(\bar{X}-\mu)/\sigma]$ for $\mu > m$, and ϕ is the probability density function of the standard normal distribution N(0,1). In addition, the remaining terms O_P/n represent the error of the expansion having a leading term of order $1/n$ in probability and can be estimated through simulation. By taking the first order of the Taylor expansion, $\hat{S}_{PK}$ can be approximated by a mathematical approach as $\hat{S}_{PK} \cong W/(6\sqrt{n}\phi(3S_{PK}))$ [7]. Moreover, Pearn and Chuang [7] obtained the critical values required for the statistical testing of process capability S_{PK} by standard simulation technique.

Capability measure for processes with single characteristic has been investigated extensively (see [9]–[11] for more details). However, capability measure for processes with multiple characteristics is comparatively neglected. In evaluating the overall process capability for processes with multiple characteristics, Chen *et al.* [12] proposed a new index, S_{PK}^T, which is a generalization of S_{PK}. According to the definition of S_{PK} in (1), for process with $S_{PK} = c$, we can obtain the process yield(%)

TABLE III
DESIGNS FOR MONTE CARLO EXPERIMENTS WITH $v = 3$ AND VARIOUS S_{PK}^{T}

No	S_{PK}^{T} =1.00			S_{PK}^{T} =1.25			S_{PK}^{T} =1.50			S_{PK}^{T} =1.75			S_{PK}^{T} =2.00		
	S_{PK1}	S_{PK2}	S_{PK3}	S_{PK1}	S_{PK2}	S_{PK3}	S_{PK1}	S_{PK2}	S_{PK3}	S_{PK1}	S_{PK2}	S_{PK3}	S_{PK1}	S_{PK2}	S_{PK3}
1	1.20	1.20	1.027	1.40	1.40	1.280	1.60	1.60	1.544	1.80	1.80	1.874	2.10	2.10	2.019
2	1.20	1.40	1.014	1.40	1.55	1.265	1.60	1.70	1.523	1.80	1.90	1.794	2.10	2.20	2.010
3	1.20	1.60	1.013	1.40	1.70	1.264	1.60	1.80	1.520	1.80	2.00	1.786	2.10	2.30	2.009
4	1.20	1.80	1.013	1.40	1.85	1.264	1.60	1.90	1.519	1.80	2.10	1.785	2.10	2.40	2.009
5	1.20	2.00	1.013	1.40	2.00	1.264	1.60	2.00	1.519	1.80	2.20	1.785	2.10	2.50	2.009
6	1.40	1.40	1.002	1.55	1.55	1.253	1.70	1.70	1.507	1.90	1.90	1.760	2.20	2.20	2.002
7	1.40	1.60	1.001	1.55	1.70	1.252	1.70	1.80	1.504	1.90	2.00	1.756	2.20	2.30	2.001
8	1.40	1.80	1.001	1.55	1.85	1.252	1.70	1.90	1.504	1.90	2.10	1.755	2.20	2.40	2.001
9	1.40	2.00	1.001	1.55	2.00	1.252	1.70	2.00	1.504	1.90	2.20	1.755	2.20	2.50	2.001
10	1.60	1.60	1.000	1.70	1.70	1.250	1.80	1.80	1.501	2.00	2.00	1.752	2.30	2.30	2.000
11	1.60	1.80	1.000	1.70	1.85	1.250	1.80	1.90	1.501	2.00	2.10	1.751	2.30	2.40	2.000
12	1.60	2.00	1.000	1.70	2.00	1.250	1.80	2.00	1.501	2.00	2.20	1.751	2.30	2.50	2.000
13	1.80	1.80	1.000	1.85	1.85	1.250	1.90	1.90	1.500	2.10	2.10	1.750	2.40	2.40	2.000
14	1.80	2.00	1.000	1.85	2.00	1.250	1.90	2.00	1.500	2.10	2.20	1.750	2.40	2.50	2.000
15	2.00	2.00	1.000	2.00	2.00	1.250	2.00	2.00	1.500	2.20	2.20	1.750	2.50	2.50	2.000

$= 2\Phi(3c) - 1$. Obviously, there is a one-to-one relationship between S_{PK} and the process yield. Considering a v-characteristic process, $P_j, j = 1, 2, \ldots, v$, is the yield (percentage of conformities) of the jth characteristic, and the corresponding S_{PK} value is $S_{PKj}, j = 1, 2, \ldots, v$. The relationship between P_j and S_{PKj} can be represented as $P_j = 2\Phi(3S_{pkj}) - 1$. To evaluate the overall process yield P, Chen *et al.* [12] proposed the following formula, $P = \Pi_{j=1}^{v}(2\Phi(3S_{PKj}) - 1)$, for $j = 1, 2, \ldots, v$. An index S_{PK}^{T} for measuring the overall process capability is $S_{PK}^{T} = \Phi^{-1}\{[\Pi_{j=1}^{v}(2\Phi(3S_{PKj}) - 1) + 1]/2\}/3$, which can be derived by $P = \Pi_{j=1}^{v}(2\Phi(3S_{PKj}) - 1)$. The index S_{PK}^{T} provides an exact measure on the overall process yield. Table I displays various commonly used capability requirement and the corresponding overall process yield associated with nonconformities parts per million (NCPPM).

Statistical testing is used to determine if a process meets the capability requirement. The null hypothesis is $H_0 : S_{PK}^{T} \leq c$ (process is not capable) and the alternative hypothesis is $H_1 : S_{PK}^{T} > c$ (process is capable), where c is the required process capability. If the point estimate of process capability exceeds the critical value c_0, the null hypothesis is rejected. Suppose that the risk of rejecting a null hypothesis is α (the chance of wrongly concluding that an incapable process is capable), the critical value c_0 can be obtained by

$$\alpha = P(\hat{S}_{PK}^{T} \geq c_0 | S_{PK}^{T} = c). \quad (5)$$

Since the exact distribution of $\hat{S}_{PK}^{T}$ is mathematically intractable, standard simulation method is performed to find the critical values for statistical testing.

1) Critical Value Determination: Monte Carlo experiments are performed to find the θth $(1 \leq \theta \leq 100)$ distribution percentiles of $S_{PK}^{T} = 1.00$, 1.33, 1.50, and 2.00 for processes with $v = 3$ characteristics using statistical software, Maple. Note that S_{PKj}, $j = 1, 2$, must be larger than S_{PK}^{T} in order to keep S_{PKj} value be a finite real number; otherwise, an infinite number is resulted. For a process with v characteristics, there are $\mathrm{H}_{v-1}^{m} = (m + v - 2)!/[(m - 1)!(v - 1)!]$ combinations in the simulation list, where m represents the size of $\{S_{PKj}, j = 1, 2, \ldots, v - 1\}$. In this case, there are a total of $\mathrm{H}_{2}^{5} = 15$ various combinations in the simulation list. The combinations we select are $S_{PKj} = 1.60(0.10)2.00$, $j = 1, 2$, which means that we examine S_{PKj} from 1.60, and by an increase of 0.10 each time, to 2.00. In addition, S_{PK3} is a value corresponding to S_{PK1}, S_{PK2} and S_{PK}^{T}. Table II lists various index S_{PK}^{T} in the domains of S_{PKj}, $j = 1, 2$ for three characteristics, and Table III lists the designs for Monte Carlo experiments with $v = 3$ and various S_{PK}^{T}. After determining the combinations for simulation, we select the process parameters (process mean μ_i and process standard deviation σ_i), which correspond to $S_{PKj}, j = 1, 2, \ldots, v$, to generate samples of Monte Carlo experiments. Random samples from normal populations

TABLE IV
SAMPLE SIZES REQUIRED FOR c_0 WITHIN THE DESIGNATED DIFFERENCES, .01(0.01)0.10

	S_{PK}^{T}				
e	1.00	1.25	1.50	1.75	2.00
0.10	40	50	-----	-----	60
0.09	-----	-----	70	80	-----
0.08	60	-----	-----	90	-----
0.07	80	90	100	-----	120
0.06	-----	100	110	120	140
0.05	100	-----	-----	130	160
0.04	110	130	140	-----	180
0.03	130	150	170	180	190
0.02	150	160	180	190	200
0.01	160	180	190	200	210

TABLE V
SIMULATED c_0 FOR VARIOUS S_{PK}^T, $n = 10(10)400$ AND $\alpha = 0.05, 0.025, 0.01$

n	1.00			1.25			1.50			1.75			2.00		
	0.05	0.025	0.01	0.05	0.025	0.01	0.05	0.025	0.01	0.05	0.025	0.01	0.05	0.025	0.01
10	1.458	1.577	1.724	1.683	1.788	1.906	1.847	1.945	2.072	2.065	2.154	2.248	2.517	2.647	2.692
20	1.323	1.408	1.516	1.639	1.720	1.808	1.840	1.908	1.994	2.053	2.131	2.217	2.415	2.512	2.628
30	1.247	1.318	1.398	1.559	1.607	1.708	1.797	1.856	1.926	2.048	2.116	2.187	2.367	2.451	2.546
40	1.216	1.263	1.326	1.515	1.574	1.656	1.765	1.821	1.891	2.037	2.090	2.168	2.333	2.403	2.478
50	1.194	1.239	1.289	1.487	1.537	1.604	1.752	1.807	1.874	2.015	2.065	2.133	2.276	2.371	2.444
60	1.169	1.208	1.259	1.461	1.513	1.563	1.739	1.789	1.843	1.997	2.046	2.103	2.286	2.343	2.421
70	1.153	1.187	1.232	1.441	1.485	1.551	1.721	1.767	1.825	1.986	2.034	2.083	2.265	2.321	2.398
80	1.144	1.173	1.223	1.427	1.469	1.523	1.708	1.750	1.803	1.976	2.024	2.067	2.251	2.305	2.379
90	1.135	1.163	1.205	1.420	1.458	1.501	1.697	1.737	1.780	1.964	2.009	2.050	2.240	2.285	2.355
100	1.129	1.155	1.192	1.410	1.445	1.485	1.689	1.726	1.770	1.954	1.995	2.040	2.230	2.272	2.335
110	1.123	1.147	1.181	1.402	1.433	1.470	1.679	1.716	1.760	1.947	1.988	2.032	2.219	2.260	2.326
120	1.118	1.141	1.173	1.395	1.425	1.460	1.670	1.705	1.745	1.941	1.982	2.026	2.209	2.251	2.309
130	1.112	1.135	1.166	1.389	1.418	1.451	1.663	1.696	1.735	1.935	1.974	2.015	2.198	2.243	2.299
140	1.107	1.129	1.158	1.384	1.412	1.443	1.656	1.688	1.726	1.930	1.968	2.006	2.192	2.236	2.290
150	1.102	1.123	1.151	1.380	1.407	1.437	1.651	1.682	1.719	1.926	1.960	1.997	2.187	2.231	2.283
160	1.098	1.118	1.143	1.375	1.404	1.430	1.647	1.677	1.711	1.920	1.953	1.990	2.181	2.225	2.276
170	1.094	1.113	1.139	1.371	1.398	1.425	1.643	1.673	1.707	1.917	1.947	1.985	2.178	2.219	2.268
180	1.092	1.111	1.136	1.369	1.393	1.420	1.637	1.667	1.702	1.913	1.942	1.976	2.175	2.213	2.261
190	1.090	1.109	1.134	1.362	1.387	1.414	1.633	1.661	1.697	1.907	1.935	1.969	2.170	2.207	2.251
200	1.087	1.106	1.128	1.359	1.383	1.408	1.629	1.656	1.692	1.902	1.932	1.964	2.167	2.201	2.245
210	1.085	1.104	1.125	1.356	1.379	1.405	1.626	1.652	1.688	1.895	1.928	1.958	2.164	2.197	2.240
220	1.083	1.102	1.123	1.354	1.376	1.402	1.623	1.649	1.683	1.890	1.924	1.956	2.161	2.195	2.235
230	1.081	1.100	1.121	1.352	1.374	1.400	1.620	1.646	1.679	1.885	1.920	1.952	2.159	2.193	2.231
240	1.079	1.096	1.115	1.350	1.370	1.396	1.618	1.643	1.673	1.844	1.916	1.947	2.156	2.190	2.226
250	1.077	1.094	1.113	1.347	1.368	1.394	1.616	1.640	1.670	1.882	1.912	1.944	2.153	2.188	2.222
260	1.075	1.091	1.110	1.345	1.365	1.390	1.613	1.637	1.667	1.880	1.909	1.939	2.151	2.184	2.217
270	1.073	1.087	1.107	1.344	1.363	1.387	1.611	1.634	1.663	1.878	1.907	1.936	1.149	2.181	2.213
280	1.072	1.085	1.105	1.342	1.360	1.383	1.609	1.631	1.659	1.877	1.905	1.931	2.148	2.178	2.210
290	1.071	1.084	1.104	1.340	1.357	1.379	1.607	1.628	1.655	1.875	1.902	1.926	2.146	2.175	2.205
300	1.070	1.083	1.103	1.339	1.356	1.376	1.605	1.626	1.652	1.874	1.900	1.924	2.144	2.172	2.203
310	1.069	1.082	1.102	1.337	1.354	1.374	1.603	1.624	1.649	1.872	1.897	1.920	2.141	2.168	2.199
320	1.068	1.081	1.101	1.335	1.352	1.372	1.601	1.622	1.646	1.870	1.894	1.917	2.138	2.165	2.196
330	1.067	1.080	1.100	1.334	1.350	1.370	1.600	1.620	1.643	1.868	1.891	1.914	2.135	2.162	2.193
340	1.066	1.079	1.098	1.333	1.348	1.368	1.598	1.618	1.641	1.866	1.888	1.911	2.132	2.159	2.190
350	1.065	1.078	1.097	1.332	1.347	1.367	1.596	1.616	1.639	1.864	1.885	1.908	2.130	2.156	2.187
360	1.064	1.077	1.095	1.331	1.346	1.366	1.594	1.614	1.637	1.862	1.882	1.907	2.128	2.153	2.184
370	1.063	1.076	1.093	1.329	1.345	1.365	1.593	1.613	1.635	1.860	1.880	1.905	2.126	2.150	2.181
380	1.062	1.075	1.090	1.328	1.343	1.363	1.592	1.612	1.634	1.858	1.878	1.904	2.124	2.148	2.178
390	1.061	1.074	1.088	1.327	1.342	1.362	1.591	1.611	1.633	1.856	1.876	1.903	2.122	2.147	2.177
400	1.061	1.074	1.087	1.326	1.341	1.361	1.590	1.610	1.632	1.855	1.875	1.902	2.121	2.146	2.176

with various parameters are generated to evaluate the estimated value of S_{PK}^T. The sample sizes are 10(10)400. Each experiment consists of 10 000 replications. After sorting the 10 000 estimated values of S_{PK}^T from the smallest to the largest of each combination, and by selecting the (100θ)th number, we can obtain the θth distribution percentile of S_{PK}^T with various combinations. Then, the c_0 values and the $100(1-\alpha)\text{th}$ distribution percentile of S_{PK}^T for various S_{PK}^T are obtained.

We note that under different fixed performance $S_{PK}^T = c$, the c_0 value is different, and the difference e between the maximum and the minimum c_0 values decreases as sample size n increases. Table IV lists the required sample size for various $e = 0.01(0.01)0.10 = 0.05$ with $\alpha = 0.05$. Note that when the sample size n exceeds 210, the difference becomes negligibly small (no greater than 0.01). Consequently, the c_0 values may be considered as a constant, which is independent of the S_{PKj} values. Since c_0 values are different under various combinations of fixed $S_{PK}^T = c$ and e, for practical purpose, we take the maximal value c_0 among the combinations for statistical testing, and this can ensure our decision makings being reliable. Table V presents the critical values c_0 for common used capability requirement $c = 1.00(0.25)2.00$ with sample size $n = 10(10)400$ and $\alpha = 0.01$, 0.025, 0.05.

2) Extension to Correlated Data: For processes with correlated characteristics, Pearn *et al.* [13] applied the principal component analysis (PCA) method to transform related variables into a set of uncorrelated linear functions of the original measurements. The approach is described briefly here.

Assume that $\mathrm{X}(v \times n)$ is a sample data matrix for process with v characteristics, where $\bar{\mathrm{X}}(v \times 1)$ is the sample mean vector of observations and $\mathrm{S}(v \times v)$ is a symmetric matrix representing the covariance between observations. $\mathrm{LSL}(v \times 1)$ and $\mathrm{USL}(v \times 1)$ represent the lower and upper specification limits, and $\mathrm{T}(v \times 1)$ represents the target values of the v quality characteristics. In addition, the spectral decomposition can be used to obtain $\mathrm{D} = \mathrm{U}^{\mathrm{T}}\mathrm{SU}$, where D is a diagonal matrix. The diagonal elements of D, $\lambda_1, \lambda_2, \ldots, \lambda_v$, are the eigenvalues of S, and the columns of U, $\mathrm{u}_1, \mathrm{u}_2, \ldots, \mathrm{u}_v$, are the eigenvectors of S. Consequently, the $i\text{th}$ principal component, PC_i, is expressed as $PC_i = \mathrm{u}_i^{\mathrm{T}}\mathrm{x}$, $i = 1, 2, \ldots, v$, where x is $v \times 1$ vectors of the original variables. The engineering specifications and target values of PC_is are $\mathrm{LSL}_{PC_i} = \mathrm{u}_i^{\mathrm{T}}\mathrm{LSL}$, $\mathrm{USL}_{PC_i} = \mathrm{u}_i^{\mathrm{T}}\mathrm{USL}$ and $\mathrm{T}_{PC_i} = \mathrm{u}_i^{\mathrm{T}}\mathrm{T}$.

TABLE VI
SAMPLE DATA OF CD, AA AND PT

	CD	AA	PT
$\bar{X}$	0.1998429	0.0750048	8999.842857
s	0.0018009	2.0299592	20.3763413
$\hat{S}_{PK}$	1.844	1.641	1.636

TABLE VII
EMPIRICAL SIZES FOR $S_{PK}^T = 1.00$ WITH SOME NON-NORMAL PROCESS DISTRIBUTIONS

n	N(0,1)	t(25)	G(22,1/6)	B(4,9)
160	0.0506	0.0638	0.0601	0.0412
180	0.0507	0.0625	0.0613	0.0422
200	0.0544	0.0630	0.0597	0.0501
220	0.0492	0.0647	0.0594	0.0465
240	0.0490	0.0611	0.0559	0.0460

TABLE VIII
EMPIRICAL SIZES FOR $S_{PK}^T = 1.50$ WITH SOME NON-NORMAL PROCESS DISTRIBUTIONS

n	N(0,1)	t(25)	G(22,1/6)	B(4,9)
190	0.0504	0.0622	0.0621	0.0441
210	0.0541	0.0620	0.0600	0.0452
230	0.0532	0.0635	0.0622	0.0445
250	0.0549	0.0614	0.0609	0.0438
270	0.0500	0.0616	0.0609	0.0463

Similarly, the relevant sample estimators, $\bar{\mathrm{X}}$ and S_2 of PC_is, can be defined as $\bar{\mathrm{X}}_{PC_i} = \mathrm{u}_i^{\mathrm{T}}\bar{\mathrm{X}}$ and $\mathrm{S}_{PC_i}^2 = \lambda_i$.

Consequently, if the characteristics are correlated, we can use the above approach to transform the correlated variables $\bar{\mathrm{X}}$ and S^2 into new variables $\bar{\mathrm{X}}_{PC_i}$ and $\mathrm{S}_{PC_i}^2$ first, and our proposed approach can proceed then.

III. PRODUCTION YIELD CALCULATION

In this study, 210 sample observations of the three parameters, CD, AA and PT, are collected from the photolithography process. By calculating sample mean, standard deviation and the estimates for S_{PK}^T (see Table VI), we can estimate that the production yield of the photolithography process is $\hat{S}_{PK}^T = 1.637$.

With risk $\alpha = 0.05$, we could use Table V to obtain c_0 for capability requirement $c = 1.75$. Since $\hat{S}_{PK}^T$ is greater than the critical value c_0, we conclude that the process meets the requirement, and the process yield is no less than 99.99932047% (equivalently, with a nonconformities of 6.8 PPM).

To show the robustness of our approach for non-normal processes, we set nominal size $\alpha = 0.05$ and evaluate the empirical size (the percentage that we reject the null hypothesis by our approach while the null hypothesis is true) by standard simulation with 10 000 replications. Tables VII and VIII show the results for process distributions with N(0,1), t(25), Gamma(22,1/6), and Beta(4,9) with various n and $S_{PK}^T = 1.00$ and 1.50. We can see that the empirical sizes are close to the nominal size; thus, we conclude that our approach is also adoptable for these process distributions. However, for processes with too skewed distribution, our approach still may not be adoptable.

IV. CONCLUSION

A good control of CD, alignment accuracy and PR thickness is critical for maintaining a high level of yield in photolithography. In this paper, we consider the yield measurement index S_{PK}^T to establish the relationship between the manufacturing specifications and the actual process performance, and provide an exact measure on process yield. A photolithography process in a semiconductor fab is investigated, and the testing process performance of CD, alignment accuracy and PR thickness measurement is considered based on the yield index S_{PK}^T. We obtain the critical values required for the hypothesis testing, using the standard simulation technique for various commonly used performance requirements. Extensive simulation results are provided and analyzed. Statistical testing can be performed to examine whether the process meets the capability requirement. The investigation is useful to the practitioners for making reliable decisions in testing the quality of an engineering lot in the photolithography process.

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