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Abstract. For a feature of finite length, linewidth roughness leads to variations in the mean feature width. Typically, numerical simulations are used to explore this relationship. An analytical approach is used. Starting with a common expression for the power spectral density, an analytical expression relating critical dimension uniformity to linewidth roughness is derived. The derived expression matches simulation results extremely well and can be used to understand more fully the detrimental impact of feature roughness on lithographic results. Finally, based on this expression, a new metric of linewidth roughness is proposed. [DOI: 10.1117/1.JMM.13.2.020501]

Keywords: critical dimension uniformity; line-edge roughness; linewidth roughness; power spectral density.

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1 Introduction

Line-edge roughness (LER) and linewidth roughness (LWR) in lithography can impact device performance in a number of ways. One of the most important impacts is also one of the easiest to understand: for a feature of finite length, the LWR results in variation in the mean linewidth [usually referred to as critical dimension uniformity (CDU)] and is thus a contributor to the sources of linewidth variation. Ma et al.[1] have shown that such linewidth variation can be significant, and today LWR is specified in the International Technology Roadmap for Semiconductors for this reason.[2] Kruit and Steenbrink[3] derived a simple model for LWR-caused CDU for electron-beam exposure, showing that CD variance was approximately inversely proportional to the length of the measured line. Lorusso et al.[4] presented a more general model for the CDU based on an exponential autocorrelation function (corresponding to a roughness exponent of 0.5).

In this paper, an analytical expression will be derived relating CDU to LWR, correlation length, roughness exponent, and the length of the feature. The expression will obviously be easier to use for this purpose than numerical simulations but will also provide insight into the scaling of feature size and roughness and the impact of roughness parameters such as correlation length on linewidth variation. Based on the insights gained from this result, a new single-valued metric of LWR or LER is proposed.

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2 Calculating Critical Dimension Uniformity from the Autocovariance

Given a randomly rough lithographic feature such as a line of length L, the CD of the feature is generally defined to be the width of the feature averaged over its length

$$\mathrm{CD}(L) = \bar{w} = \frac{1}{L}\int_0^L w(s)\mathrm{d}s, \tag{1}$$

where w is the measured linewidth at length position s and $\bar{w}$ is the mean linewidth for this feature of length L. The dependence of CD on L is made explicit by writing CD(L). The variance of the CD can be expressed as

$$\mathrm{var}[\mathrm{CD}(L)] = \frac{1}{L^2}\mathrm{var}\left[\int_0^L w(s)\mathrm{d}s\right] = \frac{1}{L^2}E\left[\int_0^L \left(w(s_1)-\bar{w}\right)\mathrm{d}s_1 \int_0^L \left(w(s_2)-\bar{w}\right)\mathrm{d}s_2\right], \tag{2}$$

where $E[x]$ is the expectation value of x, that is, the average over many instances (many features). The standard deviation (the square root of the variance) of the CD for a specific feature (in this case, a line of length L) is generally called the CDU. Adopting this terminology, we will from here on write var[CD(L)] as σ^2_{CDU}.

Changing the order of integration versus expectation value in Eq. (2),

$$\sigma^2_{\mathrm{CDU}} = \frac{1}{L^2}\int_0^L\int_0^L E\left[\left(w(s_1)-\bar{w}\right)\left(w(s_2)-\bar{w}\right)\right]\mathrm{d}s_1\mathrm{d}s_2. \tag{3}$$

The argument of this double integral is simply the autocovariance function ($\tilde{R}$) of the feature width.

$$\tilde{R}(s_1, s) = E\left[\left(w(s_1)-\bar{w}\right)\left(w(s_2)-\bar{w}\right)\right]. \tag{4}$$

Assuming the process is stationary, the autocovariance will be a function of only the distance s_1–s_2. Thus,

$$\sigma^2_{\mathrm{CDU}} = \frac{1}{L^2}\int_0^L\int_0^L \tilde{R}(s_1-s_2)\mathrm{d}s_1\mathrm{d}s_2. \tag{5}$$

Consider now, a typical form for the autocovariance: a stretched exponential:

$$\tilde{R}(s_1-s_2) = \sigma^2_{\mathrm{LWR}}e^{-(|s_1-s_2|/\xi)^{2\alpha}}, \tag{6}$$

where ξ is the correlation length, α is the roughness exponent, and σ_{LWR} is the standard deviation of the linewidth for an infinitely long line (that is, the true LWR). For $\alpha = 0.5$, this autocovariance is simply an exponential function and for this case the integrals of Eq. (5) can be evaluated analytically.

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For $\alpha = 0.5$, $$\sigma_{\mathrm{CDU}}^2 = \frac{2\xi\sigma_{\mathrm{LWR}}^2}{L}\left[1 - \frac{\xi}{L}(1 - e^{-L/\xi})\right]. \tag{7}$$

Lorusso et al.[4] presented this same result.

The nature of Eq. (7) is worth exploring. First, CDU (σ_{CDU}) is directly proportional to the LWR (σ_{LWR}). The CDU is worse for small L, and goes to zero as L approaches infinity. As is well known, the impact of line length scales with the correlation coefficient ξ so that the CDU will be poor when L approaches ξ. The ratio L/ξ can be thought of as the number of statistically independent segments making up the line length, and the variance of the linewidth is expected to be inversely proportional to this number. For example, for $L = 2\xi$, we find that $\sigma_{\mathrm{CDU}} \approx 0.75\ \sigma_{\mathrm{LWR}}$. Certainly, one important goal of LWR reduction is to reduce σ_{CDU}. As Eq. (7) shows, looking only at σ_{LWR} does not give a complete picture.

For the special case of $L \gg \xi$, Eq. (7) can be simplified to

$$\frac{\sigma_{\mathrm{CDU}}^2}{\sigma_{\mathrm{LWR}}^2} \approx \frac{2\xi}{L}\left(1 - \frac{\xi}{L}\right). \tag{8}$$

Note that this simplified expression gives a value for σ_{CDU} that is only off by 6% for the case of $L = 2\xi$, and has about a 1% error when $L = 3\xi$. Thus, the use of the simplified version will be adequate under most real-world circumstances.

3 Simulating Critical Dimension Uniformity

An LER metrology simulator (called MetroSim) has recently been described in Ref. 5. The simulation begins by generating a random rough feature that follows a predefined power spectral density (PSD),[6] then extracting $w(s)$ for a given length and sampling scheme. This allows the calculation of $\mathrm{CD}(L)$. Repeating such simulations using different random instances of the rough feature allows calculation of the CDU. For the input PSD, the Palasantzas PSD as a function of spatial frequency f is used:[7]

$$\mathrm{PSD}(f) = \frac{\mathrm{PSD}(0)}{[1 + (2\pi f\xi)^2]^{H+1/2}}, \tag{9}$$

where H plays the role of the roughness (Hurst) exponent and PSD(0) is given by

$$\mathrm{PSD}(0) = 2\sigma_{\mathrm{LWR}}^2\xi\left[\frac{\sqrt{\pi}\Gamma(H + \frac{1}{2})}{\Gamma(H)}\right]. \tag{10}$$

For the case of $H = 0.5$, this PSD function matches the autocovariance of Eq. (6) when $\alpha = 0.5$. For other values of the roughness exponent the stretched exponential autocovariance does not produce the Palasantzas PSD, though the differences are small for $\alpha \le 0.9$.

As a first test, simulations using $H = 0.5$ were performed at various values of L. For each simulation, $\mathrm{CD}(L)$ is calculated. Repeating the simulations 1,000,000 times for each L allows calculation of σ_{CDU}. To test the accuracy obtained by using 1,000,000 simulations, the case of $L = 128$ was repeated many times. The resulting CDU was found to vary by only ±0.1% (95% confidence interval). Figure 1 compares the results of the simulations to Eq. (7) for the case of $\xi = 10$ nm. For all simulations, the sampling distance $\Delta y = 1$ nm. The simulations match the predictions of Eq. (7) very well. Varying the correlation length, Fig. 2 shows the expected scaling with L/ξ. Interestingly, simulations match the analytical result when $L \ge 3\xi$. For smaller values of L, the discrete simulations diverge from the result derived from a continuous line, probably due to the biases inherent in generating a short random rough line.[6] Additionally, these results are also consistent with the simulations previously performed by Ma et al.[1] (shown in their Fig. 8).

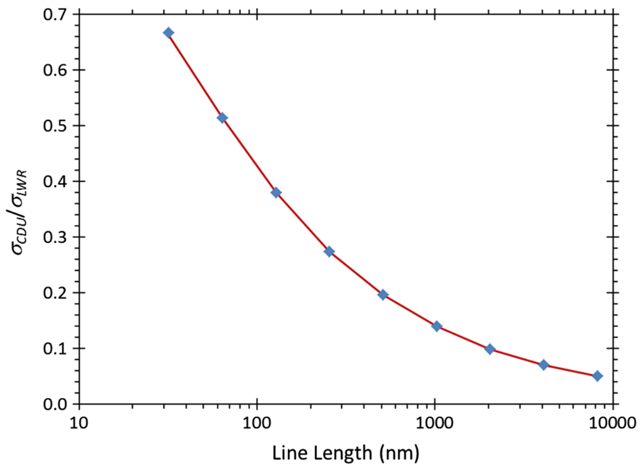

Fig. 1 Comparison of Eq. (7) (line) to simulations of critical dimension uniformity (symbols) for $\alpha = H = 0.5$, $\xi = 10$ nm, and 1,000,000 iterations for each data point.

Although the analytical expression is valid only for $H = 0.5$, simulations can be run for any value of the roughness exponent of the Palasantzas PSD. Figure 3 shows results of simulations for H varying from 0.5 to 0.9, the lithographically useful range. Empirically, Eq. (7) can be modified to account for the effect of the roughness exponent as

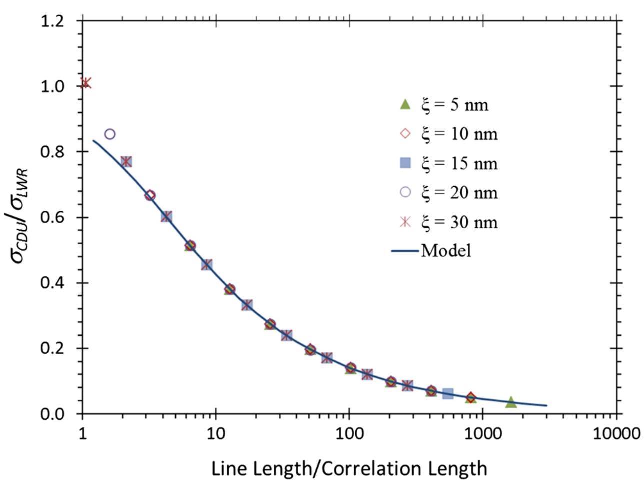

Fig. 2 Comparison of Eq. (7) (line) to simulations of critical dimension uniformity (symbols) for $\alpha = H = 0.5$, various correlation lengths, and 1,000,000 iterations for each data point.

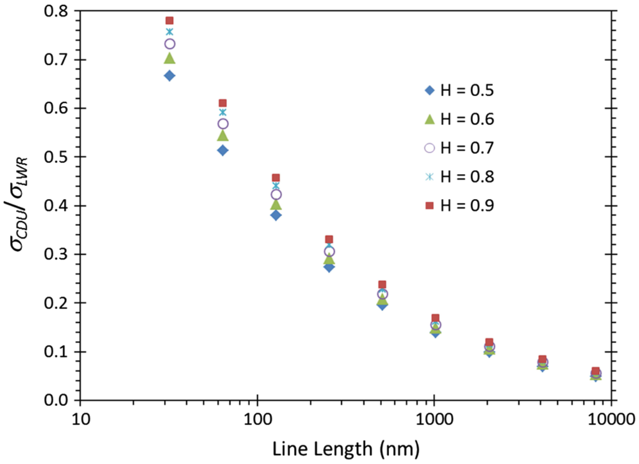

Fig. 3 Simulations of critical dimension uniformity (CDU) as a function of line length (L) and roughness exponent (H) using 1,000,000 iterations for each data point ($\xi = 10$ nm).

$$\sigma_{\mathrm{CDU}}^2 = \frac{(2H+1)\xi\sigma_{\mathrm{LWR}}^2}{L}\left[1 - \frac{\xi}{L}(1 - e^{-L/\xi})\right]. \tag{11}$$

Equation (11) matches simulations results to within 2.5% for $L \geq 3\xi$ (the worst case is when $H = 0.9$). For the case of $L \gg \xi$, this expression simplifies as before to

$$\frac{\sigma_{\mathrm{CDU}}^2}{\sigma_{\mathrm{LWR}}^2} \approx \frac{(2H+1)\xi}{L}\left(1 - \frac{\xi}{L}\right). \tag{12}$$

For all other parameters held constant, higher roughness exponent H leads to worse CDU. However, CDU is not very sensitive to uncertainty in roughness exponent. For example, if one assumes a roughness exponent of 0.5 but in fact the roughness exponent is 0.8, the error in the predicted σ_{CDU} will only be about 14%. Still, more accurate knowledge of H leads to more accurate predictions of CDU.

4 Conclusions

In this paper, an analytical expression relating CDU to LWR has been derived for the case of a roughness exponent of 0.5. For arbitrary roughness exponent H, simulations have led to an empirical modification of this analytical expression that gives sufficiently accurate results. The final expressions of Eqs. (11) or (12) can be used to predict the impact of LWR on CDU for various features (various line lengths). These expressions provide several important lessons. From a scaling perspective, node-to-node feature shrinks generally result in a constant shrink of both L and the required σ_{CDU}. In order to achieve a constant impact of LWR on CDU, both σ_{LWR} and ξ must therefore shrink in the same proportion. This has proven very hard to do. A second lesson is that the impact of LWR on CDU involves three parameters: the roughness σ_{LWR}, the correlation length ξ, and the roughness exponent H. Although the impact of H is less significant, it is clear that knowledge of σ_{LWR} without knowing ξ is insufficient to predict the impact of LWR on CDU.

Additionally, the nature of the analysis presented here suggests the possibility of a single metric for LER or LWR that reflects the impact of roughness on CDU. Consider Eq. (12), where the line length of interest is expressed as a multiple of the CD of the line being measured: $L = a\mathrm{CD}$. Keeping only the highest order term, Eq. (12) can be rearranged to become

$$\frac{\sigma_{\mathrm{CDU}}}{\mathrm{CD}} \approx \frac{1}{\sqrt{a}}\frac{\sigma_{\mathrm{LWR}}}{\mathrm{CD}}\sqrt{\frac{(2H+1)\xi}{\mathrm{CD}}}. \tag{13}$$

Let us define a dimensionless metric for LWR as follows:

$$M_{\mathrm{LWR}} \equiv \frac{\sigma_{\mathrm{LWR}}}{\mathrm{CD}}\sqrt{\frac{(2H+1)\xi}{\mathrm{CD}}}. \tag{14}$$

For $L \gg \xi$, this metric is directly proportional to the relative CDU ($\sigma_{\mathrm{CDU}}/\mathrm{CD}$) for any given value of a. Thus, the new metric represents a single number distilled from the PSD that captures everything about the PSD that contributes to linewidth variation. (An equivalent metric for LER can be obtained by using σ_{LER}). Currently, σ_{LWR} is used effectively as a single metric for roughness since it is often the only parameter reported from a measurement of roughness. The new metric defined by Eq. (14) is far superior to reporting just σ_{LWR} since it correctly accounts for the influence of H and ξ as well. It thus allows more accurate comparisons of different resists, different processes, different lithography tools, and different feature sizes in terms of LER or LWR performance. Further, practical goals can be set for M_{LWR} that reflect the need for good CDU (for example, we might require that $M_{\mathrm{LWR}} < 0.1$).

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