A New Fast Resist Model: the Gaussian LPM

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Abstract

BACKGROUND: Resist models for full-chip lithography simulation demand a difficult compromise between predictive accuracy and numerical speed.
METHODS: Using a Gaussian approximation to the shape of the image-in-resist in the region of development near a feature edge, the integral normally solved numerically in the Lumped Parameter Model (LPM) can be evaluated analytically. As a result, a well known three-dimensional resist model (the LPM) can be used in only two-dimensions (the Gaussian LPM), greatly improving speed without significant loss of accuracy.
RESULTS: For a positive resist, the image in the region of soluble resist material can be well approximated by a Gaussian image for all the mask features investigated.
CONCLUSIONS: The Gaussian LPM is expected to have accuracy similar to the LPM but with substantially greater speed.

Keywords: Lumped Parameter Model, LPM, full-chip simulation, compact resist model, optical proximity correction, OPC

I. INTRODUCTION

Many computational lithography problems require fast, accurate resist models (often called compact models) to enable lithography simulation of an entire chip in a reasonable time. While rigorous resist simulators solve physically-based models in three dimensions, compact models simplify their descriptions of the phenomena and reduce the problem to two dimensions. The result is a dramatic increase in speed, but also some loss in accuracy. Further, the resulting compact models are often more empirically than physically based, so that model parameters are hard to relate to readily observed properties of the lithography process. More importantly, though, the use of multi-parameter empirical models can produce a very good match to lithography data during calibration, while exhibiting a poorer match to experiment for other mask patterns (e.g., during model validation). The growing need for full-chip process window prediction only exacerbates these predictive accuracy problems.

One of the most commonly used compact models of resist behavior is (with many variants) the variable threshold resist model (VTR). For example, one might define a variable threshold that is a simple polynomial function of the maximum local intensity and maximum local slope near to and perpendicular to the feature edge,[1] or a polynomial function of the maximum local intensity, minimum local intensity, image slope at the mask edge, and the mask CD.[2] Usually polynomials out to second order are sufficient, and some cross terms may be included. The coefficients of these polynomials are determined empirically by comparison with experimental through-pitch CD data in a step called model calibration.

There are two main disadvantages of these empirical models. First, the accuracy of the predictions made by the VTR models are only expected to be sufficient when interpolating within the range of features used to calibrate the model. Thus, considerable effort is spent in determining the appropriate range of features used to calibrate the models and whether they are representative of any given mask design.[3,4] Second, any change in the resist process (or even the mask making process) will likely change the model coefficients in some unknown way. Thus, a change in process must be accompanied by an expensive recalibration exercise. Thus, there is a desire to use simple, high-speed compact resist models that have a more straightforward physical interpretation so that these two disadvantages can be mitigated.

In this paper a new compact resist model, called the Gaussian Lumped Parameter Model, is introduced. This model is based on the well-known three-dimensional Lumped Parameter Model (LPM), but with one dimension (the depth direction into the resist) solved analytically so that a two-dimensional model is obtained. The resulting Gaussian LPM is potentially fast enough for full-chip simulation applications, while providing physically-based resist parameters which may address some of the drawbacks of conventional compact resist models.

II. A NEW COMPACT RESIST MODEL – THE GAUSSIAN LPM

The Lumped Parameter Model (LPM) has been used when a simple model with both speed and accuracy is required.[5] This model performs a very simplified calculation of resist development in three dimensions that produces an accuracy intermediate between rigorous resist models and compact two-dimensional models such as a VTR. The LPM makes two basic assumptions: the resist contrast, γ, is independent of dose, and the path of dissolution can be segmented into vertical followed by horizontal development steps. The result is a prediction of edge position as a function of dose for a given image in resist.[6] Given an aerial image $I(x)$,

$$\left(\frac{E(x)}{E(x_0)}\right)^{\gamma} = 1 + \frac{1}{D_{eff}} \int_{x_0}^{x} \left(\frac{I(x')}{I(x_0)}\right)^{-\gamma} dx' \qquad (1)$$

Here, $E(x)$ is the dose required to put the resist edge at position x, x_0 is the position where the development path begins (for example, the center of the space in a line/space pattern), and D_{eff} is the effective resist thickness. If the center of the space is at $x_0 = 0$, then the resulting critical dimension (CD) or the space will be $2x$. There are two resist/process parameters in this model that must be calibrated: γ and D_{eff}. More advanced versions of the LPM have also been proposed.[7,8]

The numerical integration required of the LPM is too time consuming for many modeling applications. However, this integration can be carried out analytically by noting that in the clear region of an image, near the edge of a line, the aerial image (and the image-in-resist) can be well approximated as a Gaussian function.[9]

$$I(x) = I_0 e^{-(x-x_0)^2/2\sigma^2} \qquad (2)$$

Since only the space region develops away in a positive resist to form the resist profile, an accurate representation of the image is needed only in this region that develops away. Treating I_0, x_0, and σ of the Gaussian as adjustable parameters, equation (2) can readily be fit to an actual aerial image (keeping in mind that only a region near the feature edge, and particularly in the space near the feature edge, must fit well). Figure 1 shows the fit of a Gaussian to dense and isolated lines. The log-slope of the Gaussian image at any x-position is

$$ILS = \frac{d\ln I}{dx} = \frac{x}{\sigma^2} \qquad (3)$$

Thus, the log-slope varies linearly with x, a result that is approximately true for most images in the region of the space.[9]

Using the Gaussian image in the LPM equation (1) and letting the development path start at $x = x_0$ (set to zero here for convenience),

$$\left(\frac{E(x)}{E(0)}\right)^{\gamma} = 1 + \frac{1}{D_{eff}} \int_0^x e^{\frac{\gamma}{2}\left(\frac{x'}{\sigma}\right)^2} dx' \qquad (4)$$

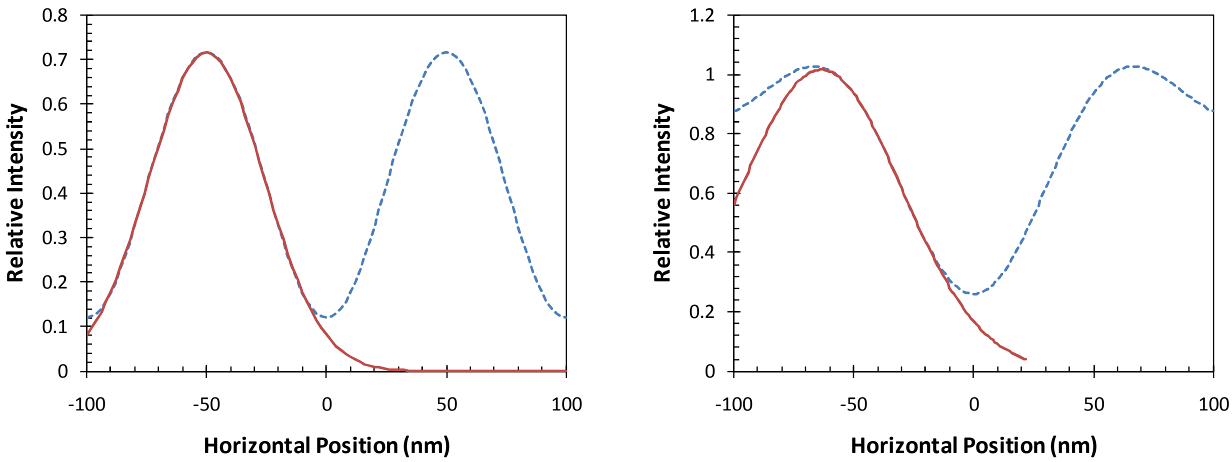
The integral is solvable in terms of the Dawson's integral[10], $D_w(z)$:

$$D_w(z) = e^{-z^2} \int_0^z e^{x^2} dx \qquad (5)$$

Dawson's integral has a maximum value of about 0.54 at $z \approx 0.92$ and asymptotically goes to $1/2z$ for large z (see Figure 2). Numerous approaches for computing or approximating Dawson's integral are available,[11,12] as are tables of values.[13] The LPM result becomes

$$\frac{I(0)E(x)}{E_0} = \left[1 + \frac{1}{D_{eff}\sqrt{g}} \left(\frac{I(x)}{I(0)}\right)^{-\gamma} D_w\left(\sqrt{g}\, x\right)\right]^{\frac{1}{\gamma}} \qquad (6)$$

where E_0 is the resist dose-to-clear, and $g = \dfrac{\gamma}{2\sigma^2}$.



(a) (b)

Figure 1. Fit of a Gaussian (solid line) to image-in-resist (dashed lines) for (a) dense and (b) isolated mask patterns (NA = 1.2, λ = 193nm, Dipole 0.8/0.3 Y-polarized illumination, 50nm line feature, binary Kirchhoff mask).

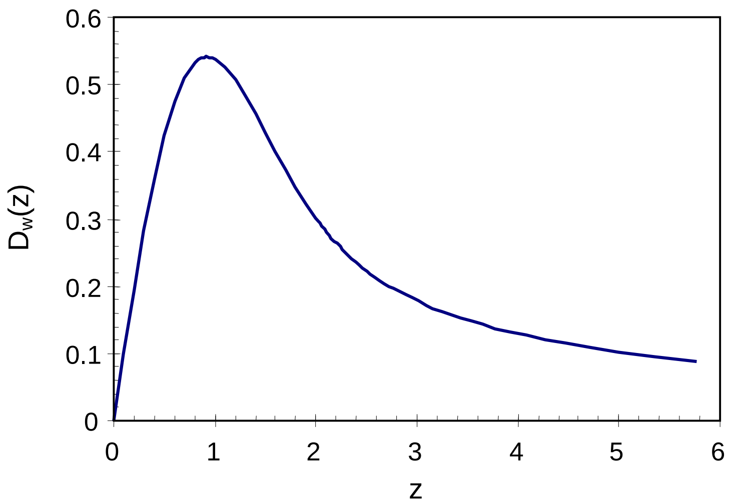


Figure 2. A plot of Dawson's Integral, $D_w(z)$.

III. USING THE GUASSIAN LPM

In the form of equation (6), the Gaussian LPM predicts the dose required to give a particular CD. To be useful for OPC applications, the model must be inverted to give the CD (or rather, the x-position of the resist edge) obtained for a given dose. First, the dose is calibrated to give the proper feature size for the chosen reference feature. Using the Gaussian fit of the image for this reference, we calculate the quantity

$$\left(\frac{E}{E_0}\right)^{\gamma} = \text{constant} \qquad (7)$$

Using the Gaussian image of equation (2) in equation (6) and rearranging, we have the form of the Gaussian LPM ready to be inverted:

$$D_{eff}\sqrt{g}\left[I_0^{\gamma}\left(\frac{E}{E_0}\right)^{\gamma} - 1\right] = e^{gx^2} D_w\left(\sqrt{g}\,x\right) \qquad (8)$$

The left-hand side takes on a numerical value for a given calibrated process and Gaussian image. The right hand side of equation (8) can be tabulated as a function of $\sqrt{g}\,x$. Thus, the value of x (the edge position) can be found by simple interpolation within the table. A plot of this interpolation data is shown in Figure 3.

The accuracy of the Gaussian LPM depends on two things: the accuracy with which a Gaussian function fits an image in the region of development near a feature edge, and the accuracy of the LPM itself. The accuracy of the LPM has been previously discussed.[14] Both topics require further characterization using actual mask designs and wafer data.

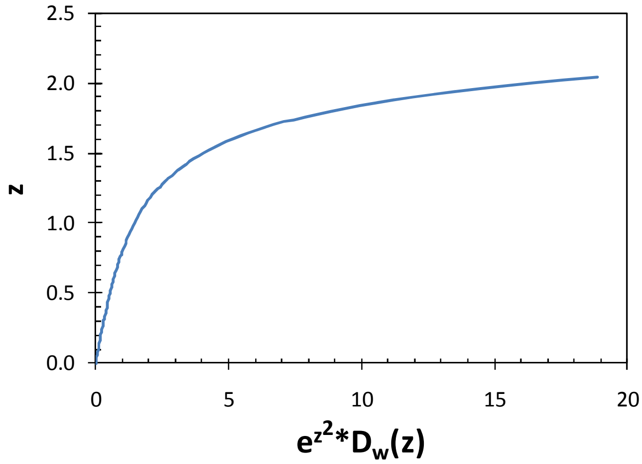


Figure 3. A plot of the interpolation data needed to solve equation (8).

IV. CONCLUSIONS

The Gaussian LPM provides a convenient and accurate way to convert the three-dimensional Lumped Parameter Model into a two-dimensional model that is far more practical for full-chip lithography simulation. The model works by first fitting a one-dimensional slice of the image-in-resist (perpendicular to the feature edge) to a Gaussian, extracting three image parameters. Then, using a resist model with two parameters, the edge position of the resist edge is extracted from the Gaussian LPM model of equation (8). In this way, the Gaussian LPM works like a more physically rigorous variable threshold model. Techniques commonly used in OPC software to account for non-development resist effects, such as convolution of the image with a diffusion blur function, can easily be applied to the Gaussian LPM as well. Validation of this model for both sufficient speed and sufficient predictive accuracy for OPC applications has yet to be performed.

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