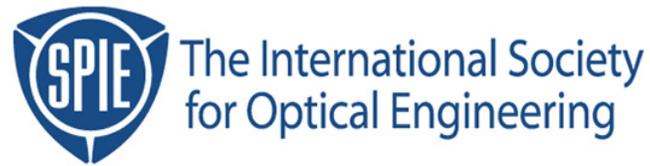


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Automatic Calibration of Lithography Simulation Parameters

Sven Jug, Richard Huang, Jeffrey Byers, Chris Mack

FINLE Technologies, A Division of KLA-Tencor
8834 N. Capital of Texas Hwy, Suite 301, Austin, TX 78759
sven.jug@kla-tencor.com

Abstract

A method is presented for automatically adjusting the input parameters of a lithography simulator to more accurately match a given set of experimental conditions. Using contrast curves, swing curves or focus-exposure matrices, simulation parameters are automatically modified in a search to minimize the difference between the simulated results and the experimental data. The algorithms used are described, as well as their robustness and sensitivity to experimental noise. Results of these tuning procedures are presented and the tuned set of parameters is shown to give good quantitative agreement of simulation to experiment.

Keywords: *lithography simulation, model calibration, PROLITH, AutoTune*

I. Introduction

For many applications, lithography simulation has proven extremely effective at predicting or explaining important lithographic trends, providing insight and direction for problem solving, and extrapolating lithographic technology into the future. For some applications, however, the usefulness of lithography simulation depends on its ability to match experimental results for a specific process. When simulation and experiment do not match, there are three possible reasons. First, the experimental results could be wrong due to setup, process, and/or measurement errors. Second, the models used in the simulator may not adequately describe the physical realities present in the experiment. And third, the input parameters used for the simulation may not adequately describe the actual experimental conditions. Of these three, incorrect input parameters is by far the most common source of simulation to experiment mismatch in optical lithography modeling.

Recently, a systematic approach to matching simulation to experiment for a given process, called “tuning” the model, was proposed [1-3]. In this paper, the approaches described earlier will be expanded and automated. By examining contrast curve, swing curve (reflectivity, dose to clear and critical dimension), and focus-exposure matrix data sets, a variety of tunable lithographic simulation parameters can be estimated. A systematic approach to calibrating specific parameters will be provided and many examples given for both conventional and chemically amplified resists.

Many input parameters are known based on relative, uncalibrated measurements made in the fab. For example, the resist thickness value that the typical lithographer measures is usually not an absolute measure of resist thickness. This is due to the fact that most fabs have no means available to calibrate their resist thickness measurements to any absolute standard. In fact, fab measurements of resist thickness do not need to be absolute for the purposes of manufacturing – a relative resist thickness is all that is necessary. In the case of the swing curve, this inaccurate measurement results in a shift in the phase of experimental swing curve data relative to the simulation. The model’s phase can be shifted to account for the measurement method by adjusting the resist’s index of refraction setting in the simulation.

As another example, experimental results often do not match up with the simulated results due to inaccurate dose calibration. Like the resist thickness measurement tool, dose meters do not usually yield absolute measurements and are really only needed to provide relative measurements (dose matching among steppers, etc.).

In fact, dose meters can vary as much as 20% from meter to meter. Therefore, the meter used to dose check the stepper used in the experiment typically does not match the meter used when the resist company measured their Dill ABC parameters. Because of this, dose to size and dose to clear values can be off between simulation and experiment. The model can be adjusted in dose to match the experiment by changing the C parameter (representing the exposure rate constant) of the Dill ABC parameters to match the lithographer's process and account for the difference in dose calibration.

As a third very common example, hotplate temperatures during the post-exposure bake (PEB) of chemically amplified resists can have a very significant impact on feature size. However, the hotplate "set point" and the actual wafer time/temperature profile can be quite different [4]. Calibration between hotplates in a fab is a necessary exercise. Likewise, calibrating the virtual hotplate of the simulator to the hotplate used in the fab is also needed. This can be done by adjusting one or more of the rate constants for the chemical reactions that occur during PEB.

Development parameters are another source of potential mismatch between simulation and experiment. Develop model parameters are often measured by the resist manufacturer for their recommended process. However, the process used in the fab is often different, sometimes in subtle ways like a different temperature, other times in obvious ways like the use of a different developer. Tuning the development parameters can account for these differences. Other parameters can also be adjusted for fine tuning of the model such as lens aberrations and the CD metrology method.

This paper will seek to define a procedure whereby a lithographer can use an automated parameter adjustment method to tune the parameters of the model to a given set of experimental data. Then, using the adjusted parameters, one can accurately model many other photolithography processes (for example, the same resist on differing substrates, using different masks, different stepper settings, and under other conditions) thereby saving time, money, and making use of the full potential of the modeling tool. These techniques will be demonstrated through the use of PROLITH v7.0 and Klarity ProDATA with the AutoTune™ module.

II. Theory

A starting point for lithographic simulation calibration is usually to run a simulation and manually change some parameters in a way that the match between real and simulated data improves. For this method to work a good understanding of the model theory and a good intuition is required by the user. The user must also decide on a criterion for a good match. A commonly practiced way to decide on the quality of the match is plotting the two curves in one graph and eyeballing the difference. The results become very subjective.

Auto-tuning introduces a systematic and automated approach for both varying simulation parameters and evaluating the quality of the match. It also opens the door for varying multiple simulation parameters at once, which is difficult to do properly when done manually.

The basis for an auto-tuning algorithm is the metric for the difference between the real and the simulated data. It determines how well the agreement is between the two curves. A standard approach for this can be taken from the domain of data modeling. It uses the "least-squares" merit function

$$c^2(\mathbf{a}) = \sum_{i=1}^N \left[\frac{y_i - y(x_i, \mathbf{a})}{s_i} \right]^2 \quad (1)$$

as a metric for the goodness of fit between data and model. Here N is the number of data points, $\{y_i, x_i\}$ is the set of experimental data points, \mathbf{a} is the set of adjustable parameters, σ_i is the noise estimate for measured point i, and $y(x_i, \mathbf{a})$ is the model simulated function for point i. χ^2 evaluates to smaller values for more agreement and to larger numbers for less agreement between the real and simulated data. The goal is to find simulation parameters, which minimize χ^2 . A related merit function is the root-mean-squared (RMS) error function.

$$\Sigma(\mathbf{a}) = \sqrt{\frac{\mathbf{c}^2(\mathbf{a})}{N}} = \sqrt{\frac{1}{N} \sum_{i=1}^N \left[\frac{y_i - y(x_i, \mathbf{a})}{s_i} \right]^2} \quad (2)$$

Minimizing χ^2 also minimizes Σ but using Σ allows comparison of fits between datasets of different sizes. In the case of a reflectivity swing curve χ^2 would be obtained by subtracting the simulated reflectivity values from the measured values at each given resist thickness and adding up all squared differences.

The second component of auto-tuning is the algorithm that finds those simulation parameters that cause χ^2 to reach a minimal value. This problem can be approached in different ways and again the domain of data modeling offers well established solutions. This paper will consider two algorithms. Both of them converge to a local minimum within the given parameter ranges. They cannot find a global minimum that is located on the other side of a maximum from the current parameter set guess. Therefore, a reasonable initial guess for the parameters is required.

The first algorithm is called the grid method. It takes as an input a range for each of the simulation parameters that are subject to optimization (variable parameters) and a fixed value for all the remaining simulation parameters (fixed parameters). In the first step we generate M equally spaced points for each of the N variable parameters. As a consequence we have M^N different sets of simulation parameters that can be used for a simulation. These sets correspond to an N -dimensional grid with M points in each dimension. All of the sets have their parameters within the required ranges. In the second step we pick a starting set (initially the middle of the grid) and run simulations for the starting set and its closest neighbor sets in the grid (3^N simulations). Each of the simulations results in a value for χ^2 . If the parameter set with the smallest χ^2 is the starting set, the algorithm is finished. If a different set has the smallest χ^2 , this set becomes the new starting set and step 2 gets repeated. The desired set of simulation parameters is found when the algorithm stops repeating step 2.

This algorithm can be varied in many ways in order to achieve performance enhancements. One variation is the two-step grid method, running the grid method twice in a row. The first time it uses the input ranges as given and finds the optimum (minimum χ^2). The second time it takes the result from the first run and repeats the calculations within smaller ranges that have been specified around the result from the first run. In this way more accuracy can be achieved without unnecessary simulations in areas of little interest.

The second algorithm is a variation of the Levenberg-Marquardt (L-M) method [5], which is a well-known algorithm from the domain of data modeling. The inputs are a first guess for the parameters that will be optimized and fixed values for all remaining parameters. The algorithm assumes that χ^2 is quadratic with respect to each parameter and can be computed at any neighboring parameter set ($\mathbf{a} + \mathbf{d}$) using a Taylor series expansion.

$$\mathbf{c}^2(\mathbf{a} + \mathbf{d}) = \mathbf{c}^2(\mathbf{a}) + \mathbf{d} \nabla \mathbf{c}^2 + \frac{1}{2} \mathbf{d} \cdot \mathbf{H} \cdot \mathbf{d} \quad (3)$$

where \mathbf{H} is the Hessian matrix (defined below). If equation 3 is valid locally then the location of any minimum relative to the current set of parameters can be solved from the matrix equation.

$$\mathbf{a}_{\text{next}} = \mathbf{a} + \mathbf{H}^{-1} \cdot \nabla \mathbf{c}^2(\mathbf{a}) \quad (4)$$

where $(\nabla \chi^2)_k$ and H_{kl} and are expanded as

$$(\nabla \chi^2)_k = \frac{\partial \chi^2}{\partial a_k} = -2 \sum_{i=1}^N \frac{[y_i - y(x_i, \mathbf{a})]}{s_i^2} \cdot \frac{\partial y(x_i, \mathbf{a})}{\partial a_k} \quad (5)$$

$$\mathbf{H}_{kl} = \frac{\partial^2 \chi^2}{\partial a_k \partial a_l} \approx 2 \sum \frac{1}{s_i^2} \cdot \frac{\partial y(x_i, \mathbf{a})}{\partial a_k} \cdot \frac{\partial y(x_i, \mathbf{a})}{\partial a_l} \quad (6)$$

Equation 4 is applied iteratively to improve the current guess of the optimized parameter set. In the rare cases where equation 4 results in a larger χ^2 than the current value, the Levenberg-Marquardt routine seamlessly switches to a steepest-descent algorithm that guarantees χ^2 improvement by modifying the diagonal elements of the Hessian matrix \mathbf{H} . Convergence is based upon successive iterations yielding a non-significant improvement in χ^2 .

This algorithm is a robust iterative approach that improves the variable simulation parameters with fast convergence. However, it assumes that the partial derivatives (equations 5 and 6) of the modeling function are known. For the type of data discussed in this paper the partial derivatives with respect to each fitting parameter are too complex to calculate analytically. Therefore, a finite difference approximation to each partial derivative is used and constitutes the bulk of the computation time for the algorithm.

In most cases the L-M method is the better choice between the two algorithms. It converges faster and requires fewer simulations per iteration, which makes a noticeable difference in performance. However, the grid method offers a very robust alternative, because the algorithm's basic concept does not depend upon partial derivatives. This can be useful when the parameters that are tuned have nontrivial correlations (see below).

A typical state of the art resist model has between 10 and 20 parameters. How one should approach fitting lithographic data largely depends upon what is the desired goal from the fitting process. If simple data fitting for one particular dataset is desired then adding parameters to the list of adjustable parameters until a satisfactory fit is achieved is reasonable. However, if comparison of the resist parameters between two different datasets or extendibility of the optimized resist parameter set to predict future lithographic results is desired, then a more judicious, physically based choice of adjustable fitting parameters is required.

Choosing which parameters to adjust for data fitting requires some understanding of the interaction of these parameters with each other and the type of data being fit. First, some resist parameters affect only certain types of output data. For instance, the resist develop rate does not change the resist reflectivity. Choosing to fit reflectivity data by varying any parameter other than the optical parameters (A + B and refractive index) results in much slower convergence at best and failure of the algorithm to converge at worst. In either case the "optimized value" of the resist develop rate obtained from this fit will be no better than the original value. A further discussion of parameters effect the various data types will be given in the example calibrations section.

A more subtle issue for parameter choice originates from inter-parameter correlation. Some resist parameters show mild to severe correlation with each other when fitting lithographic data. Increasing one parameter can be offset by decreasing or increasing another parameter while achieving a similar if not equal χ^2 . In mathematical terms these parameters are either non-orthogonal to each other in the extreme case or the data set is mildly "under-determined" in the less extreme case. The under-determined data set does not cover enough process space to significantly distinguish the various solutions obtainable. Severe correlation is easily found in the two Dill parameters A and B, the bleachable and unbleachable absorbance parameters. In all but the most extreme conditions (very high exposure dose or very thick resists) it is difficult to distinguish between these two absorbance parameters using Resist CD data. Figure 1 shows a resist CD swing curve simulation for several values of A and B using a typical I-Line resist model. For all resist thickness values below 1000nm the four curves are fairly indistinguishable. The values were chosen by first changing A from the original value (0.8) and then increasing B until a reasonable match was found. Clearly with any measurement noise it would be impossible to determine the correct values of A and B from this type of data.

A useful way to view parameter pair correlations for a particular dataset is to plot χ^2 in a contour plot, while varying the two parameters of interest. Figures 2 and 3 show the correlation plots for a mildly correlated and an uncorrelated parameter pair resulting from focus-exposure matrix data. In Figure 2 the Dill C parameter is shown to be correlated with the Development N (Mack model contrast-like parameter). Although a minimum is found for this data set, the resulting χ^2 contour resembles a shallow valley oriented diagonally. Changes in either

parameter independently result in a larger χ^2 but a small increase in C coupled with a small increase in N results in an equivalent χ^2 . Figure 3 shows that for the same dataset the Dill C parameter is not correlated with the diffusivity parameter (given by the logarithm of the Arrhenius coefficient, $\ln(A_{\text{Diffusivity}})$). The χ^2 contour shows a definite single optimal solution. For noisy data the affect of parameter correlation becomes more of an issue since the difference between near degenerate solutions must be greater than the noise level to definitively say one solution is better than the other. Parameter correlation does not reduce the quality of the fit, χ^2 , but rather it reduces the confidence in the resulting parameters.

III. Example Calibrations

When testing data fitting routines the success of any algorithm will depend upon its ability to fit data in the presence of experimental anomalies such as random noise and/or missing data points. To test the previously described calibration algorithms, “experimental” data was generated from known solutions by adding noise to simulated data and throwing away points at random. This adds two of the common complexities found in real data yet maintains the known answer underlying the “experimental” data. The quality of the fit can then be judged based upon not only the goodness of fit but also upon how close the optimized parameters are to the “true” values.

In generating the test cases, three different resist models were employed, each representing typical resists from I-Line (Shipley SPR 500), DUV (Shipley UV6) and 193nm (Sumitomo PAR710). These resists were chosen for their wide variation in parameter sets and general familiarity throughout the semiconductor industry. The input resist parameters for each resist are given in Table 1. The types of data generated were CD Swing curves, Contrast Curves, and Focus-Exposure matrix . Experimental noise was added to the datasets using

$$s_{\text{CD-Swing}} = \text{Rndu}() \cdot s_{\text{measure}} + \text{Rndu}() \cdot s_{\text{dynamic}} \cdot \left| \frac{\partial \text{CD}}{\partial \text{Thickness}} \right| \quad (7)$$

$$s_{\text{Contrast}} = \text{Rndu}() \cdot s_{\text{measure}} + \text{Rndu}() \cdot s_{\text{dynamic}} \cdot \left| \frac{\partial \text{CD}}{\partial \text{Exposure}} \right| \quad (8)$$

$$s_{\text{CD-FE}} = \text{Rndu}() \cdot s_{\text{measure}} + \text{Rndu}() \cdot s_{\text{dynamic}} \cdot \left| \text{CD} - \text{CD}_{\text{Target}} \right|^2 \quad (9)$$

where $\text{Rndu}()$ is a uniform random number generator with range $-1.0 < \text{Rndu}() < 1.0$. The first term of each equation represents a measurement noise and the second term introduces a dynamic noise representative of a process error (e.g., coating non-uniformity).

The most basic calibration experiment involves swing curve data. This can be in the form of resist reflectivity, Dose-to-Clear or resist CD as a function of resist thickness. In general swing curve data derived from resist CD at constant dose is the most accessible and accurate type of swing curve data. Consequently, we shall specifically address this type of swing curve, though the parameter calibration methodology would be similar using reflectivity or Dose-to-Clear data. As discussed in the introduction, CD swing curve data is useful for removing two of the most common errors in matching simulation to experiments: inconsistent thickness measurement techniques and the dose calibration of imaging tools. The goal is to offset all of the dose calibration or systematic thickness errors by modifying two or three of the resist parameters [1], effectively eliminating the simulation mismatch.

The shape and response of swing curve data is most directly affected by the resist refractive index (n), absorbance (A and B) and the resist exposure rate constant C . Figure 4 shows a CD swing test case generated from the SPR 500 resist model in Table 1. Approximately 7.4 nm of RMS noise was added to the simulated

points using equation 7. Also shown in Figure 4 are the simulation results using incorrect values of A, C and resist refractive index. Using the Levenberg-Marquardt algorithm, the three parameters were adjusted in 5 iterations to achieve the agreement shown in Figure 5. The RMS error between the fit and the noisy data was 6.5, which is in good agreement with the amount of noise originally added. The “true” parameter, original starting point and converged parameters are given in Table 2. Again, the converged parameters show good agreement with the original correct parameter set.

An interesting exercise is to run through the calibration procedure as a function of the added noise level. The same set of simulated data with added noise and resist parameter calibration was performed 5-10 times at each noise level. The RMS error for parameter calibration was calculated using the randomly generated sets at each noise level. The resulting parameter calibration error is shown in Figure 6 as a function of the added noise level. As can be seen the expected error in calibrated parameters gets progressively worse with increasing noise level. Even so, the relative maximum error in both A and C is approximately 10% for the highest noise level added. This 30nm RMS CD noise level is much worse than what one would expect to see in practice. The accuracy in the refractive index calibration on a relative scale by comparison is even less at under 0.2% error for the 30nm RMS CD error.

The second type of experimental data that is useful for parameter calibration is contrast curves. The remaining resist thickness after develop is measured as a function of open field exposure dose. From this type of data, several develop parameters are easily calibrated. Among them is the minimum develop rate, the threshold PAC concentration for the Mack model type resists, and the developer contrast-like parameter. Figures 7 and 8 show the results of calibrating these develop parameters for the I-Line resist SPR-500 and the DUV resist UV-6. The data for calibration was obtained by adding noise to known simulation results. The original and resulting calibrated parameters are likewise given in Tables 3 and 4. Note that the parameter correlation of development contrast and dissolution inhibition is quite strong for contrast curves [6].

Whereas swing curve data is well suited for the calibration of the optical parameters, and contrast curves are amenable to the calibration of several develop parameters, focus-exposure matrix data is sensitive to most of the 10-20 resist parameters. Consequently a wider range of resist parameters may be considered adjustable to achieve a good match between experiments and simulation. With so many parameters, the issues of parameter correlation as discussed earlier must be considered. Tables 5 and 6 list the most important parameters for FE matrix calibration as well as a general guideline for the correlation level between these parameters. Table 5 describes the parameters most often used for conventional positive tone resists and Table 6 lists the parameters for chemically amplified positive tone resists. By eliminating the parameters which show large correlation effects with other parameters the list of parameters to calibrate is drastically reduced. The corollary is that it is only possible to calibrate this limited number of parameters simultaneously with any degree of confidence. When two particular parameters are correlated one can choose to calibrate either one. It is logical to calibrate the parameter that is not already known with some degree of certainty.

From this list, three parameters (C, the diffusivity, and develop contrast) were chosen for calibration using the same test case procedure and FE matrix data. The chemically amplified DUV and 193nm resists given in Table 1 were both chosen for this test. The results of this calibration is shown in Figures 9 and 10 and Tables 7 and 8.

V. Conclusions

A method has been presented for automatically adjusting the input parameters of a lithography simulator to more accurately match a given set of experimental conditions. Using contrast curves, swing curves or focus-exposure matrices, simulation parameters were automatically modified in a search to minimize the difference between the simulated results and the experimental data. The algorithms used were described and tested using controlled datasets. These dataset were generated from simulations but have controlled amounts of noise added. By varying the noise level added the robustness and accuracy of the calibration procedure to experimental noise was tested. Results of these tuning procedures have been presented and the tuned set of parameters has been shown to give good quantitative agreement with the correct values.

References

1. S. H. Thornton and C. A. Mack, "Lithography Model Tuning: Matching Simulation to Experiment," *Optical Microlithography IX, Proc.*, SPIE Vol. 2726 (1996) pp. 223-235.
2. M. E. Mason, R. A. Soper, R. M. Terry, and C. A. Mack, "Process-specific Tuning of Lithography Simulation Tools," *Optical Microlithography X, Proc.*, SPIE Vol. 3051 (1997) pp. 491-498.
3. C. A. Mack, M. Ercken, M. Moelants, "Matching Simulation and Experiment for Chemically Amplified Resists," *Optical Microlithography XII, Proc.*, SPIE Vol. 3679 (1999) pp. 183-192.
4. M. D. Smith, C. A. Mack, and J. S. Petersen, "Modeling the Impact of Thermal History during Post Exposure Bake on the Lithographic Performance of Chemically Amplified Resists," SPIE Vol. 4345 (2001).
5. W.H. Press, S.A. Teukolsky, W.T. Vetterling, B.P. Flannery, Numerical Recipes The Art of Scientific Computing, 2nd Edition, (1992) , Cambridge University Press.
6. C. A. Mack, "Lithographic Optimization Using Photoresist Contrast," *KTI Microlithography Seminar, Proc.*, (1990) pp. 1-12, and *Microelectronics Manufacturing Technology*, Vol. 14, No. 1 (Jan. 1991) pp. 36-42.

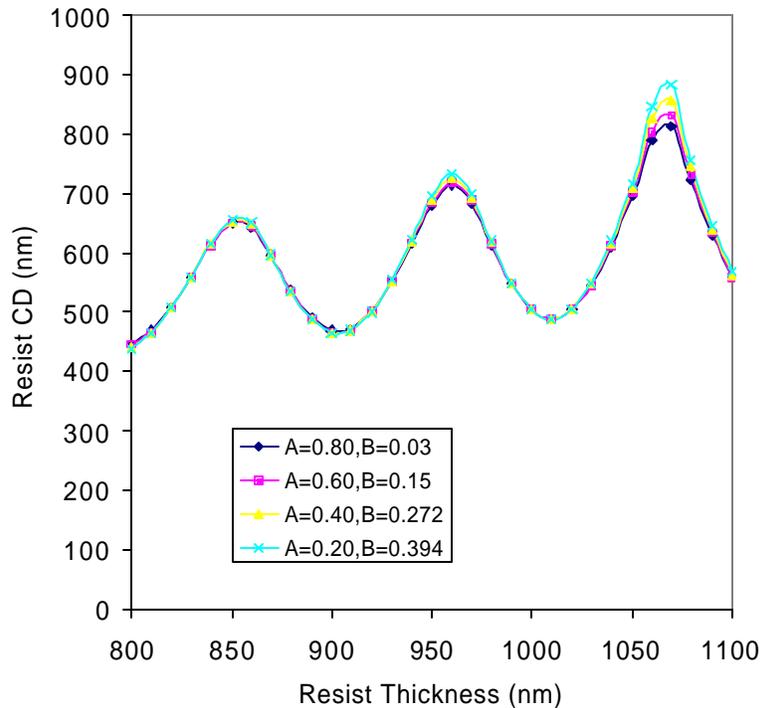


Figure 1: Simulated Resist CD swing curve for various A and B parameter combinations. Simulation condition = 500 nm nested line/space using 365 nm exposure at 0.5 NA and SPR 500 resist parameters except as noted for A and B.

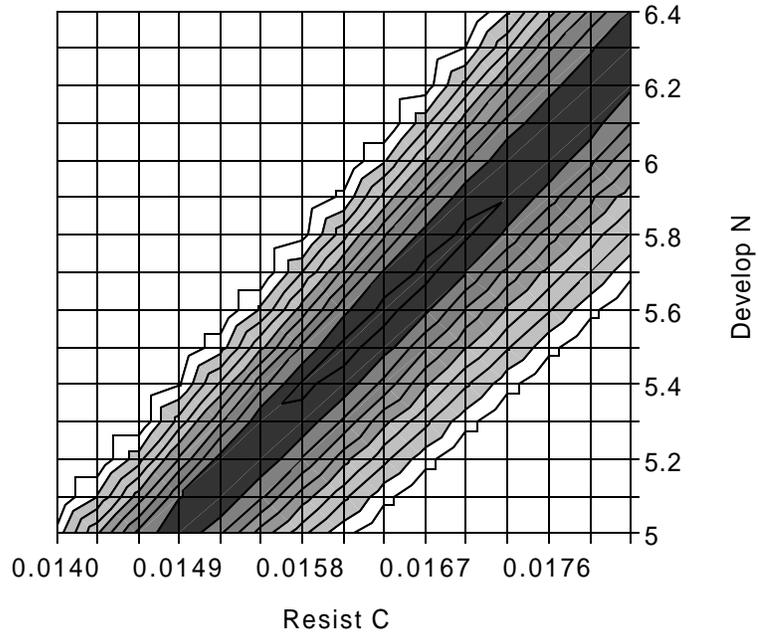


Figure 2: Contour plots for χ^2 versus Resist C and Develop N for noisy FE matrix data. Simulation condition = 500nm nested line/space using 365nm exposure at 0.5 NA and SPR500 resist parameters except as noted for C and Develop N.

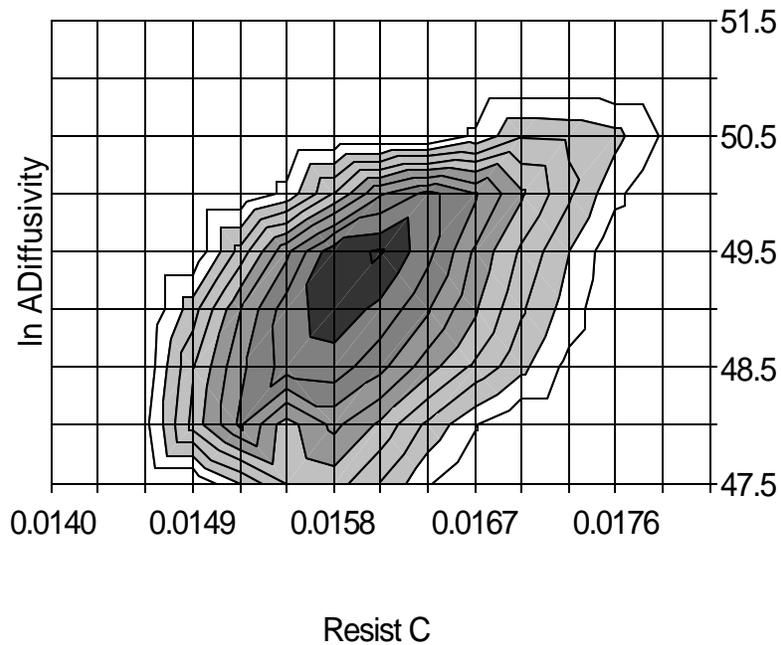


Figure 3: Contour plots for χ^2 versus Resist C and $\ln(A_{\text{Diffusivity}})$ for noisy FE matrix data. Simulation condition = 500nm nested line/space using 365nm exposure at 0.5 NA and SPR500 resist parameters except as noted for C and $\ln(A_{\text{Diffusivity}})$.

Table 1. Input resist parameters used to generate test case data.

Resist Name	SPR 500	UV6	PAR 710
Resist Vendor	Shipley	Shipley	Sumitomo
Resist Type	Positive Conventional	Positive CA	Positive CA
Developer Model	Mack	Mack	Enhanced Mack
Development Rmax (nm/s)	120	4050	550
Development Rmin (nm/s)	0.1	0.4	0.05
Development Mth	-100	0.7	-
Development Resin	-	-	550
Development n	5.44	23	12
Development l	-	-	12
Surface Development Rate	0.1	0.005	0.195
Inhibition Depth (nm)	100	560	220
Thermal Decomp. Ea(kcal/mole)	34.32	0	0
Thermal Decomp. ln(Ar) (1/s)	36.8	-20	-20
PEB Diffusivity Ea (kcal/mole)	35	30	16.9
PEB Diffusivity Ln(Ar) (nm ² /s)	49.53	41.3	24.52
Room Temperature Acid Diff. Length (nm)	-	0	0
Amplification Reaction Order	-	1	1
Relative Quencher Concentration	-	0.098	0.125
PEB Amplification Ea (kcal/mole)	-	32.221	16.946
PEB Amplification Ln(Ar) (1/s)	-	36.923	18.987
PEB Bulk Acid Loss Ea (kcal/mole)	-	0	0
PEB Bulk Acid Loss Ln(Ar) (1/s)	-	-20	-20
PEB Acid Evaporation Ea (kcal/mole)	-	0	0
PEB Acid Evaporation Ln(Ar) (1/s)	-	-20	-20
PEB Diffusion-Controlled Reaction Ea (kcal/mole)	-	0	0
PEB Diffusion-Controlled Reaction Ln(Ar) (1/nm ²)	-	20	20
A (1/um)	0.84	0	0
B (1/um)	0.03	0.5	1.23
C (1/mJ)	0.016	0.063	0.0236
Unexposed Refractive Index	1.7098	1.746	1.699
Exposed Refractive Index	1.7098	1.746	1.699

Entries denote with a - are not used for this resist.

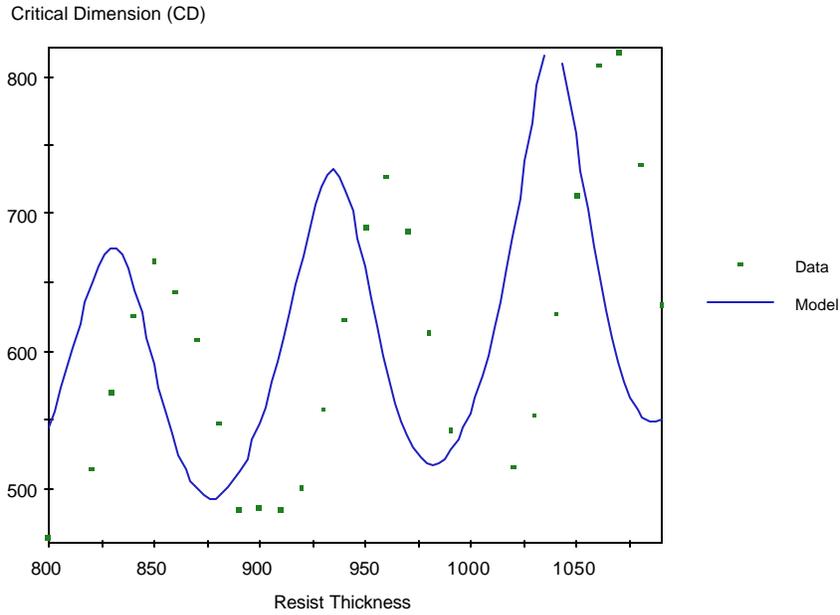


Figure 4: Graph of CD swing curve test case data and simulation using unoptimized resist parameters. $C = 0.015$, $A = 0.8$, Unexposed Refractive Index= 1.80 . Simulation condition = 500nm nested line/space using 365nm exposure at 0.5 NA and SPR500 resist parameters except as noted for C , A and $n_{unexposed}$.

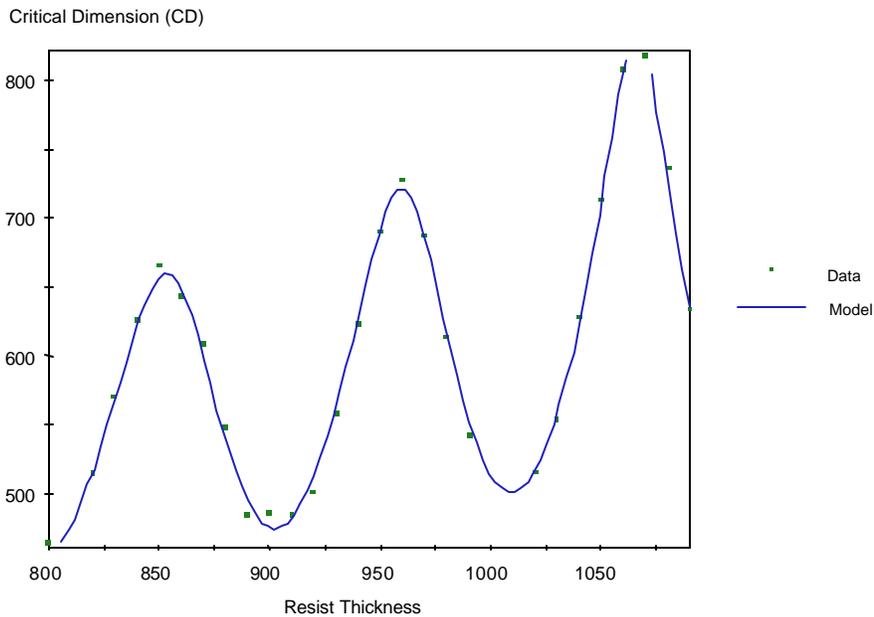


Figure 5: Graph of CD swing curve test case data and simulation using optimized resist parameters. $C = 0.0161$, $A = 0.8633$, Unexposed Refractive Index= 1.7121 . Simulation condition = 500nm nested line/space using 365nm exposure at 0.5 NA and SPR500 resist parameters except as noted for C , A and $n_{unexposed}$. RMS added noise = 7.4 nm.

Table 2 : AutoTune starting, target and final resist parameter results for SPR500 CD swing curve data.

Parameter Name	Starting Value	Target Value	Final Value
Rate Constant C (cm ² /mJ)	0.015	0.016	0.0161
Unexposed Refractive Index (real)	1.80	1.7098	1.7121
Abs. Parameter A (1/um)	0.80	0.84	0.8633
RMS χ^2 Error	127.5	7.4	6.5

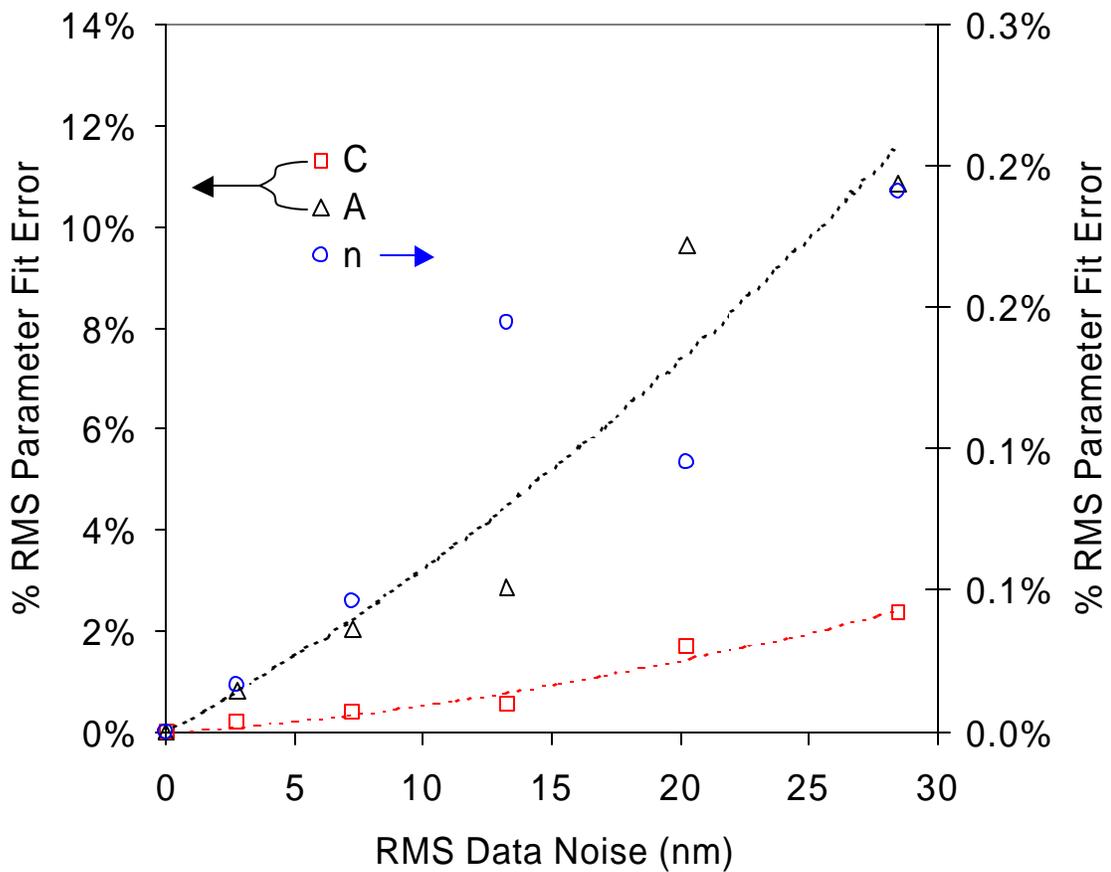


Figure 6: Graph of parameter calibration error versus noise level in data. Simulation condition = 500nm nested line/space CD Swing Curve using 365nm exposure at 0.5 NA and SPR500 resist parameters. Resist thickness = 800-1100 nm.

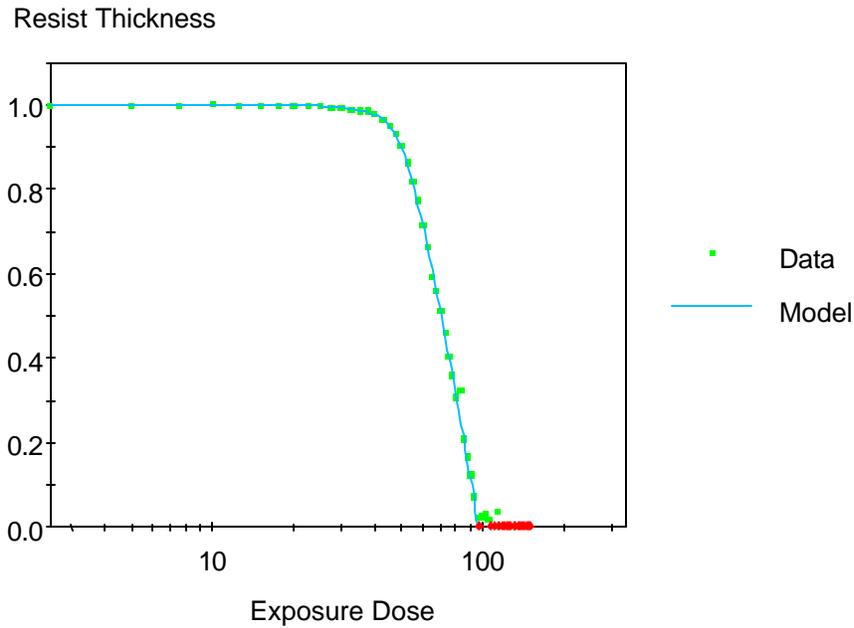


Figure 7: Contrast curve graph of relative resist thickness remaining for SPR 500 test case data and simulation using optimized develop parameters: $R_{\min} = 0.14$ nm/s, $R_n = 5.44$. Simulation condition = 365nm exposure at 0.5 NA and SPR500 resist parameters except as noted for R_{\min} and R_n . RMS added noise = 0.013.

Table 3 : AutoTune starting, target and final resist parameter results for SPR500 Contrast curve data.

Parameter Name	Starting Value	Target Value	Final Value
Develop Rmin	0.2	0.1	0.14
Develop N	6.0	5.44	5.44
RMS χ^2 Error	0.071	0.013	0.013

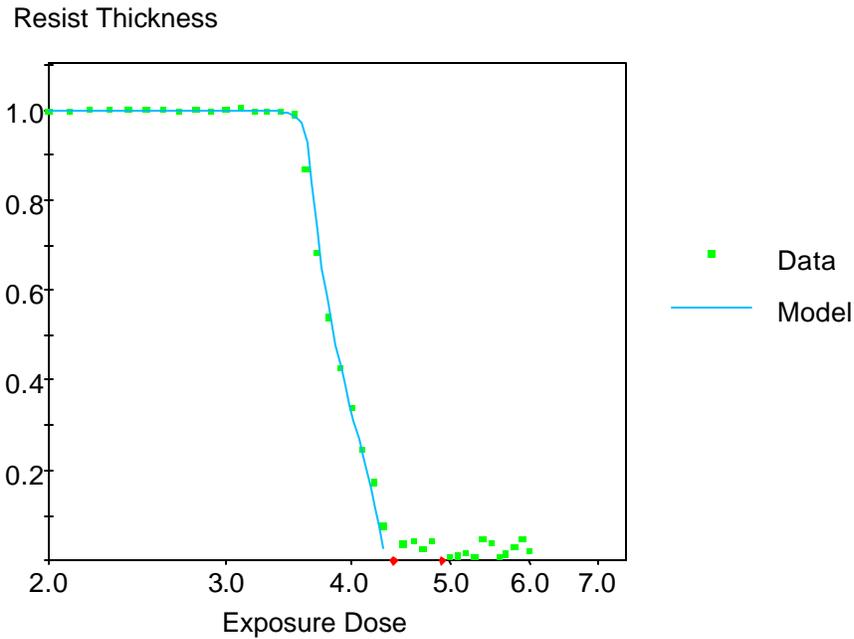


Figure 8: Contrast curve graph of relative resist thickness remaining for UV6 test case data and simulation using optimized develop parameters: $R_{min} = 0.1$ nm/s, $R_n = 18.0$ and $R_{mth} = 0.68$. Simulation condition = 248nm exposure at 0.63 NA and UV6 resist parameters except as noted for R_{min} , R_n , and R_{mth} . RMS added noise = 0.022.

Table 4: AutoTune starting, target and final resist parameter results for UV6 Contrast curve data.

Parameter Name	Starting Value	Target Value	Final Value
Develop Rmin	0.2	0.4	0.1
Develop N	20	23	18
Develop Mth	.6	0.7	0.68
RMS χ^2 Error	0.29	0.022	0.026

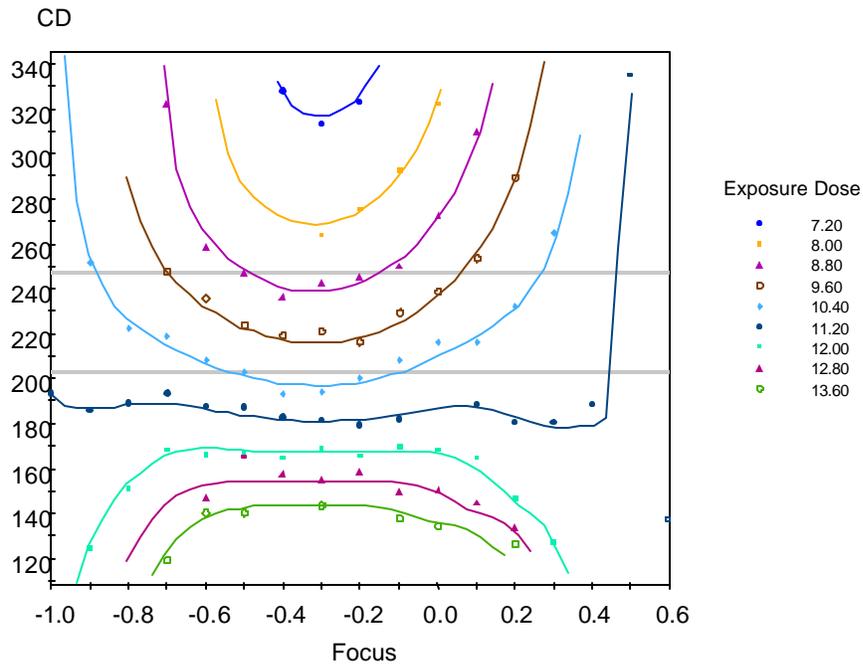


Figure 9: Focus Exposure Matrix plot for UV6 test case data and simulation results using optimized develop parameters: $C = 0.0628$, $\ln(A_{\text{Diffusivity}}) = 41.36 \text{ nm}^2/\text{s}$, and $R_n = 22.2$. Simulation condition = 225nm L/S features using 248nm exposure at 0.63 NA and UV6 resist parameters except as noted for C , $\ln(A_{\text{Diffusivity}})$, and R_{min} . RMS added noise = 27.1 nm.

Table 7: AutoTune starting, target and final resist parameter results for UV6 Focus-Exposure matrix data.

Parameter Name	Starting Value	Target Value	Final Value
Rate Constant C (cm ² /mJ)	0.06	0.063	0.0628
PEB Diffusivity Ln(Ar) (nm ² /sec)	41.7	41.3	41.36
Development n	23.5	23	22.2
RMS χ^2 Error	57.5	27.1	24.3

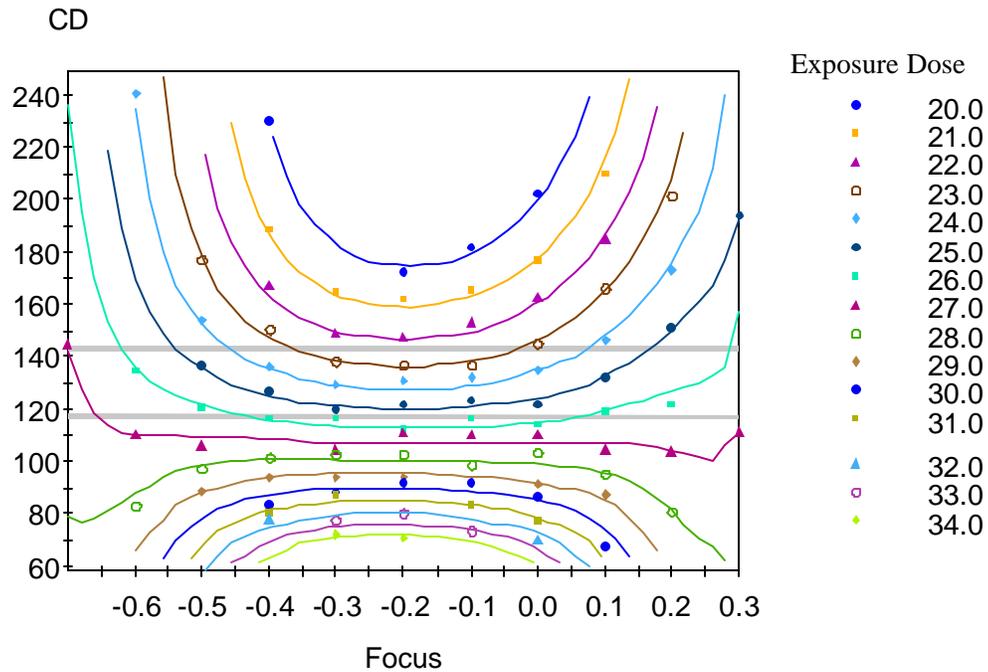


Figure 10: Focus Exposure Matrix plot for PAR 710 test case data and simulation results using optimized resist parameters: $C = 0.0248$, $\ln(A_{\text{Diffusivity}}) = 24.66 \text{ nm}^2/\text{s}$, and $R_1 = 12.80$. Simulation condition = 130 nm/320 nm L/S features using 193nm exposure at 0.63 NA and PAR710 resist parameters except as noted for C , $\ln(A_{\text{Diffusivity}})$, and R_{min} . RMS added noise = 7.6 nm.

Table 8: AutoTune starting, target and final resist parameter results PAR710 Focus-Exposure matrix data.

Parameter Name	Starting Value	Target Value	Final Value
Rate Constant C (cm ² /mJ)	0.025	0.0236	0.0248
PEB Diffusivity $\ln(A_r)$ (nm ² /sec)	24.5	24.52	24.66
Development l	14	12.0	12.80
RMS χ^2 Error	36	7.6	6.2