PHOTOMASK

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PM15 3rd Place Best Paper

MPC model validation using reverse analysis method

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ABSTRACT

It became more challenging to guarantee the overall mask Critical Dimension (CD) quality according to the increase of hot spots and assist features at leading edge devices. Therefore, mask CD correction methodology has been changing from the rule-based (and/or selective) correction to model-based MPC (Mask Process Correction) to compensate for the through-pitch linearity and hot spot CD errors.

In order to improve mask quality, it is required to have accurate MPC model which properly describes current mask fabrication process. There are limits on making and defining accurate MPC model because it is hard to know the actual CD trend such as CD linearity and through-pitch owing to the process dispersion and measurement error. To mitigate such noises, we normally measure several sites of each pattern types and then utilize the mean value of each measurement for MPC modeling. Through those procedures, the noise level of mask data will be reduced but it does not always guarantee improvement of model accuracy, even though measurement overhead is increasing. Root mean square (RMS) values which is usually used for accuracy indicator after modeling actually does not give any information on accuracy of MPC model since it is only related with data noise dispersion. In this paper, we reversely approached to identify the model accuracy. We create the data regarded as actual CD trend and then create scattered data by adding controlled dispersion of denoting the process and measurement error to the data. Then we make MPC model based on the scattered data to examine how much the model is deviated from the actual CD trend, from which model accuracy can be investigated. It is believed that we can come up with appropriate method to define the reliability of MPC model developed for optimized process corrections.

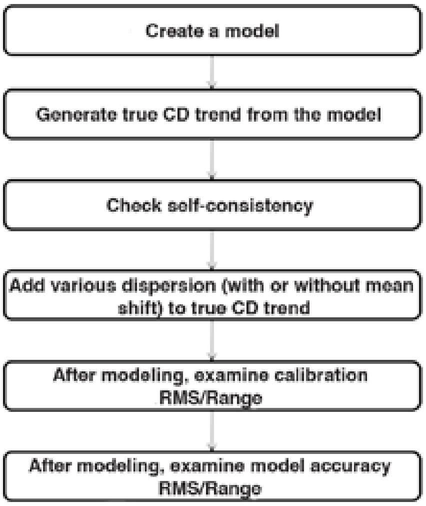

Figure 1. The procedure of reverse analysis method to validate the MPC model.

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EDITORIAL

Photomasks Today - How to Pay: Less Science, More Scheduling

Artur Balasinski, Cypress Semiconductor

The recent 2015 edition of BACUS Photomask Symposium featured a lot of outstanding papers in support of more-Moore. But there was the invisible elephant in the room, so aptly described in this Newsletter's Editorial just 3 months ago by Infineon's Thomas Struck: there is a business aspect of this business. Somebody has to make money to allow all these lofty papers on EUV to continue. And this business part barely deserved any mention, let alone a session in a Photomask Conference. Interesting. Let me play devil's advocate for the next two paragraphs.

There were the "good old days" when even Ford Motor wanted to have their semiconductor division. But now we live in the (presumably) "bad, new days," when companies are either desperately getting rid of their semiconductor Jurassic Parks or consolidating them. This makes all the high-cost research worth not much more than the paper they are printed on - for the enduser. Again, in the "good, old days", the question was, can we make it? In the "bad, new days", the issue is: sure, we can make it, but so what. Is there volume production willing to support it? Because then, and only then, we can realistically talk about EUV, multiple-patterning, and other things exciting those with full heads but empty pocket-books.

Back in the "good old days", it took less than $100k to sponsor a game-changing startup. In the "bad, new days" one can't move without $100M (a tribute to Moore?). Looking without prejudice at some titles of BACUS papers makes me think of an alternative, like an "IG" BACUS meeting, covering mirror issues to those of the actual BACUS. For example, the "IG" BACUS version of "EUV lithography scanner and mask optimization for sub-8nm" would be, "How many 8 nm EUV scanners are really out there and who knows how to make money off of them anyway"? Or, opposing the "EUV mask infrastructure readiness and gaps for TD and HVM" paper, there would be, "What on Earth is the EUV mask infrastructure and what does one know about it running 1 lot a year?" The paper on "EUV Litho and Mask Challenges" could be preceded by "Why is this even important and who has the money to pay?" etc.

But getting more serious now, how can we improve the lives of those rowing with the other slaves? Why not a paper "How to ensure 100% Process Predictability of the Good Old 65 nm Binary Mask?". Or, "Rule Based OPC: How not to Spend More than 30 Seconds Thinking of It". Thomas Struck made it clear: many tools are 15+ years old. That should make them ~100% predictable like the old Chevys. Yet, when running a tapeout, there is always a question, how much time would a maskshop need to deliver? The name of the game is time to market, now more than ever. The fanciness is no longer a valor, it is the predictability, as with all the aging disciplines. By addressing both the ascending and the descending aspects of our business, we would not only keep a sound balance, but make the "bad, new days" become the "good, new days."

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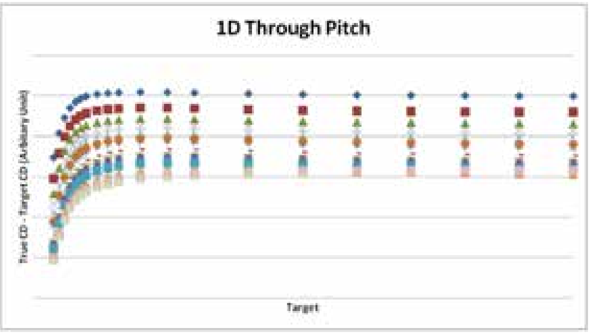


Figure 2. True CD trend.

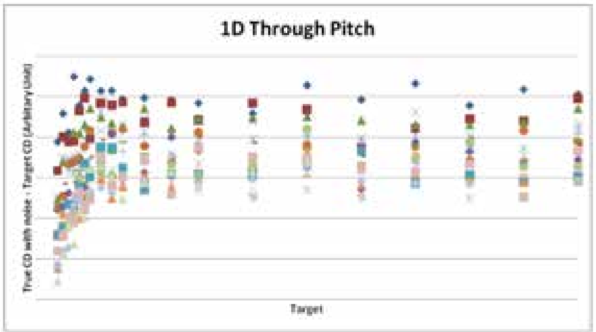


Figure 4. Dispersive data of σ 1.7nm. Comparing to figure 2, CD trend looks the same but each data are highly noisy.

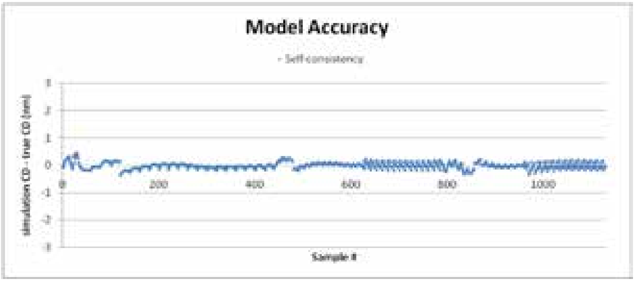


Figure 3. Self-consistency result. If the modeling is ideal, all value should be 0. Each RMS and range is about 0.115nm and 0.8nm. Calibration RMS and model accuracy RMS is the same in self-consistency test. X axis denotes sample index (1D : 1~455, Dot : 456~623, Hole : 624~791, Line End Tip to Tip : 792~960, Space End Tip to Tip : 961~1129).

1. Introduction

The required mean-to-target (MTT) specification of a mask is becoming tighter as design node is getting smaller. To satisfy this requirement and make quality mask, model-based MPC[1, 2], which compensates the through-pitch linearity, is applied.

The accuracy of the measurement is essential for building a proper MPC model. To obtain accurate data by reducing noise, the averaged value, instead of using a CD measured from single site, collected from several different sites is applied. Measuring more points is helpful in achieving this goal. On the other hand, these additional measurements are time consuming job since hundreds or thousands types of patterns are commonly used for modeling. To balance between accuracy and cost, the proper analysis is required. However, since it is impossible to know the exact CD values without any noise, it is also impossible to compare the level of degradation of accuracy caused by that of data. In this paper, we employed reverse analysis method to overcome this difficulty. We reversely assumed that all the exact CD values are already known and controlled noise is imposed on them. By using these virtual data, the reliability and the limitation of a model can be revealed. The detail of the method is shown in section 2 and the simulation results are explained in section 3.

2. Procedure

Figure 1 shows the procedure of the reverse analysis method. First, a MPC model is created with typical simulation parameters and it is assumed that the model perfectly represents the process. Thus, the generated CD values by the model are regarded as exact CD or true CD as displayed in figure 2. Since the true CD data are generated by a model, if the calibration process is ideal, almost the same model should be retrieved. This, self-consistency, is checked to use its accuracy as a baseline of the calibration. The RMS of the calibrated model turned out to be 0.115nm and the range to be 0.8nm. Figure 3 shows the difference between the true CD value and the predicted CD value by the model.

Various dispersions (with or without mean shift), which are generated under Gaussian normal distribution, are then added to the true CD data for emulating errors from process and measurement. After calibrating a model with dispersive data, calibration RMS and model accuracy RMS are examined. Calibration RMS, which is conventionally regarded as model accuracy, is defined as the value that calculated from the deviation between model simulation data and dispersive data; on the contrary, model accuracy RMS, which denotes real model accuracy, is defined as the value that calculated from the deviation between model simulation data and true CD data.

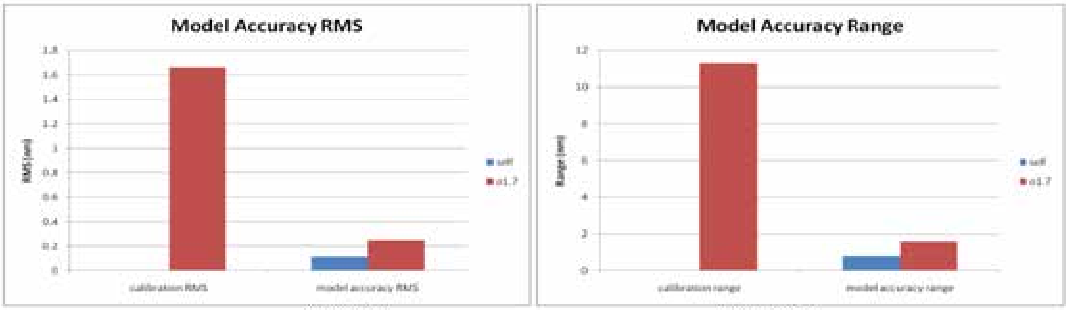
3. Results

3.1 Model accuracy influenced by standard deviation (σ) 1.7nm noise

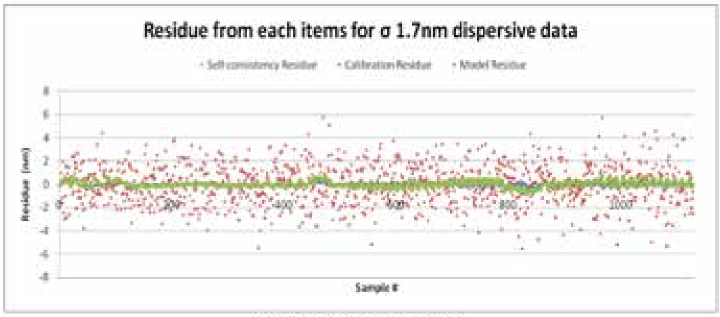
Figure 4 shows the dispersive data of σ 1.7nm. Its trend resembles figure 2 but each values are different. After calibration, we checked the calibration RMS and model accuracy RMS under above procedure. Calibration RMS is about 1.66nm. At a glance, it looks like we find bad model because of a large calibration RMS. However, by virtue of controlled dispersion, it is easy to say calibration RMS is just the dispersion scattered on the true CD data as two values are almost the same.

Model accuracy RMS is 0.249nm which is not far from the self-consistency RMS 0.115nm and it denotes that even though there is σ 1.7nm noise, accurate model is created as you can see in figure 5. Additionally, comparison between model range and model accuracy range as the same manner as RMS also supports the above analysis. By enumerating each data as shown in figure 5(c), it is easy to see the model behavior. The red dot denotes the residues after modeling and its uniform distribution shows that it is the given noise σ 1.7nm. The blue dot denotes self-consistency result which is the baseline of model calibration. The green dot denotes model accuracy result and it is almost the same as blue dot.

However, the number is just dispersion. The real accuracy is



(a) RMS (b) Range



(c) Enumerated Data

Figure 5. Each data after calibration; (a) Calibration RMS is 1.66nm so it is easily regarded as the model is imperfect.

model accuracy RMS 0.249nm, and it is highly close to the self-consistency RMS. It means that accurate model is created. (b) In the point of range view, model accuracy is reviewed. (c) By enumerating each data, it is easy to see the model behavior. The blue dot denotes self-consistency result which is the baseline of model calibration. The red dot denotes the residues after modeling, which can be considered as noise from process or measurement. The green dot denotes model accuracy result and it is almost the same as blue dot.

3.2 Model accuracy influenced by various noises

Various dispersive data are used to examine the relation between data dispersion and model accuracy more clearly. In other words, it has been known that the best way to increase the model accuracy is to use average data from several different sites. The purpose of this is to reduce the dispersion which makes the data more close to the actual. For example, dispersion σ 0.54nm can be achieved by averaging 10 data which has dispersion σ 1.7nm and statistically it follows the formula $\sigma/\sqrt{n}$; n is the number of measurements. Thus, if we know the relation between data dispersion and model accuracy, it will be helpful to mitigate the cost for additional measurements.

As shown in figure 6, the calibration RMS reveals dispersion it holds as mentioned in section 3.1. Thus, calibration RMS cannot be an index for good model. It is just the index for continuing calibration or not. If it is saturated enough, the model accuracy will be similar regardless of the level of dispersion. Model accuracy RMS and range support this fact that the level of dispersion is not critical factor on model accuracy; when the baseline of each model accuracy RMS and range are 0.115nm and 0.814nm, model accuracy RMS ranges from 0.121nm to 0.35nm and model accuracy range varies from 0.844nm to 2.15nm according to the dispersions.

Actually this result is considerably reasonable if we understand the modeling. During calibration, it minimizes the errors of given data. Mean value of errors are minimized to be 0, so the RMS is naturally the dispersion because the data used in these experiments above have uniformly distributed noise; so it may be easy to find a solution.

Noise level can be different according to the type or density of the patterns and stability of process or metrology machine. Therefore, it is emulated with simply mixed dispersion. A model is created with calibration RMS 2.04nm which is similar with total error. Calibration found out the input dispersion and made a accurate model. Not only total dispersion and mean value, but also those for each type of patterns are analyzed as shown in figure 7.

3.3 Model response to the mean shift errors and noise

Above test shows that finding an actual trend in the scattered data is properly-performed. In this section, the model accuracy dependence on mean shift errors is examined. Mean shift errors can happen because there can be CD offset between 1D patterns and 2D patterns. It comes from the measurement of 2D patterns since it is more dependent on the region of interest (ROI) size than that of 1D patterns because of corner rounding effect. And this is not compatible with current calibration which does not take the corner rounding effect into account. For example, as shown in figure 8 when measuring 1D pattern, if ROI size is not too small, the measurement result is similar, while measurement result of 2D pattern is changed by ROI size. Corner rounding area that is involved in ROI during measurement influences on the 2D measurement results. For stable reproducibility of measurements, ROI is usually selected to be large.

Even though 2D measurement is dependent on the definition, it is true for who uses that definition. Therefore, it should be covered by model. To understand the offset effect on model, data of 2D patterns are shifted such as figure 9.

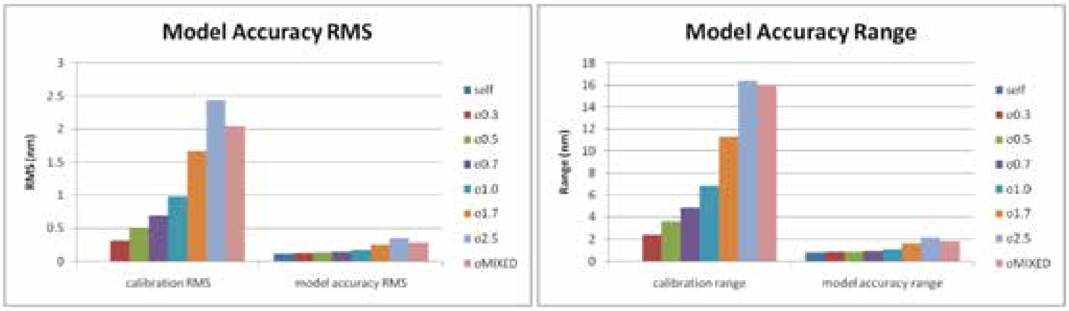
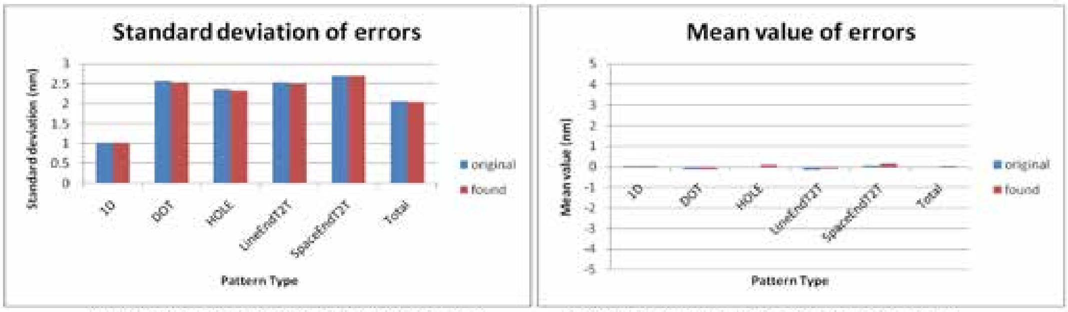


Figure 6. The model accuracy is almost the same regardless of level of dispersion. Model accuracy RMS/range of σ 2.5nm data is 0.35nm / 2.15nm and it is not greater than self-consistency accuracy RMS/range 0.115nm/0.814nm.



(a) Original and model-found dispersion (b) Original and model-found mean value

Figure 7. In case of the data having mixed dispersion, total and individual standard deviations and mean values between original and found noise are similar. That guarantees accurate model.

In figure 10, self-consistency result shows that it is almost impossible to find a model that describes mean shift errors. Even though there is no dispersion, RMS is already 1.02nm. Especially, 1D data also failed to be described by model. Mean shift is incompatible to current calibration so that the main factor of model degradation is the mean shift.

Its occurrence can be explained by the modeling algorithm as mentioned in section 3.2. If there are large errors unexplainable by model, some points should compensate for their errors to make total mean value 0. So it can happen that trustful 1D data are also distorted as shown in figure 10. Figure 11 shows simplified example of this phenomenon.

To prevent this distortion of model, it is strongly required to have more kernels that can compensate for the systematic error of mean shift. Current fundamental form of model is Gaussian distribution based on the physical phenomenon such as behavior of a bunch of electrons for e-beam writing and plasma for etching. However, there is artificial but inevitable systematic error so that model should be enhanced to explain this kind of errors.

There is another option to remove these phenomena. Since the mean shift errors originated from artifact, mismatch between measurement and calibration, it can be overcome by ROI free measurement. ROI free measurement is achieved by using scanning electron microscope (SEM) contour since it is natural and equivalent to the 1D measurement. During calibration, the model that most similarly describes SEM contour itself will be selected. There have been tries and endeavors on creating model with SEM contour.[3, 4, 5] However, it looks like it is not yet ready for production. To achieve this, SEM business as well as MPC business should work together to improve the maturity of this technology. As shown in figure 12 and 13, the uniform distributions of errors and mixed errors are applied to mean shifted true CD data, and then model accuracy of them is investigated. Model accuracy for each kind of dispersions is similar to the model accuracy of self-consistency model. These results together with the results of section 3.2 summarize that dispersion effect on model accuracy is very small and mean shift is more dominant and manifest that additional measurements are not necessary under this situation.

In case of mixed dispersion with shift errors, as shown in figure 14, found total and individual standard deviations and mean values are not properly matched with the given original errors. Calibration algorithm looks like only considering total errors to be minimized. If it works by each type of patterns, the model distortion can be reduced.

3.4 Model features of different MPC tool

Reverse analysis method is applied to another MPC tool. The overall results shown in figure 15 are similar to the previous. The strength and weakness are not much different from each other. Kernel improvement or SEM contour calibration which explains or remove the mean shift and calibration by each type of patterns will give the difference.

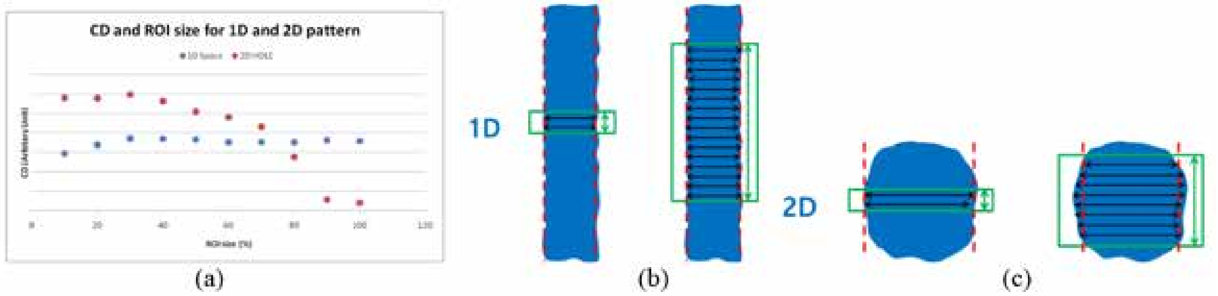


Figure 8. The effect of the ROI size on 2D pattern; (a) The graph shows that 2D measurement results are severely dependent on the ROI size. (b) For 1D pattern, ROI size greater than proper size, the LER error is averaged out so that measurement results do not count on the ROI sizes. (c) For 2D pattern, if ROI size is large, due to variation of the corner rounding area, the measured CD changes.

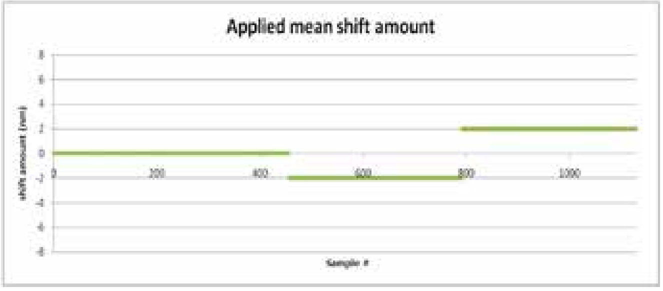


Figure 9. Applied mean shift amount.

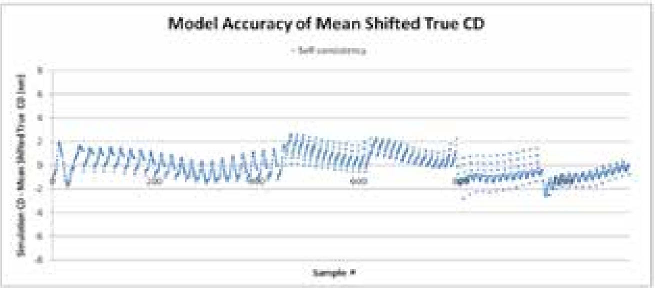


Figure 10. Self-consistency of mean shifted true CD trend. RMS is 1.02nm.

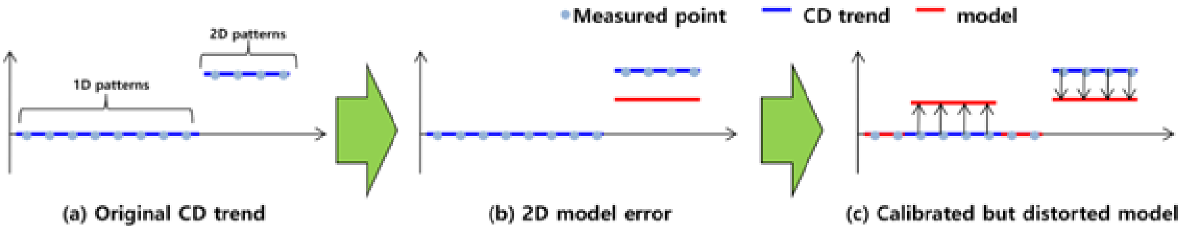


Figure 11. Simple explanation of the model distortion; if model cannot explain mean shift as shown in (b), then trustful data as well as mean shifted points are distorted to make their residue average be 0.

4. Conclusions

In this paper, we studied the model applying reverse analysis method. Starting from exact or true CD data and comparing them with modified data from various conditions including uniform noise, mixed noise, shift error and combination of them, model revealed its features, strength and weakness.

Model is relatively robust from noise level so that measuring additional points for reducing the noise is inefficient. The main reason for model degradation is due to mean shift error mostly from the mismatch between calibration and the measurement of 2D patterns caused by corner rounding effect. New kernel or ROI-free measurement can be a solution for the model error. However, the root cause is mainly come from artificial effect, the latter is most recommended. SEM contour itself is natural and equivalent to 1D patterns such that current Gaussian kernel can describe the process. Calibration algorithm should be refined for better model building. Partial minimization of errors by each type or category of data should replace the overall minimization of errors.

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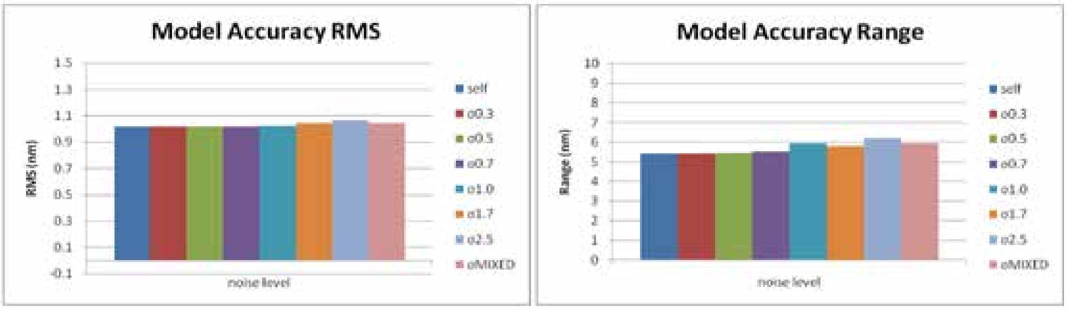

Figure 12. Model accuracy of given mean shifted true CD data. Regardless of noise, model accuracy is not too different. There is below 1nm change in model accuracy range.

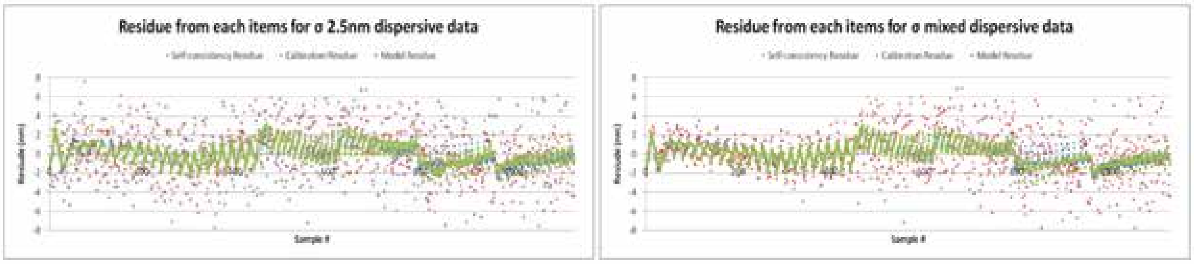

Figure 13. Model comparison between uniform error (σ 2.5nm) and mixed error. Regardless of error type, the guaranteed accuracy is almost the same as the accuracy of self-consistency model.

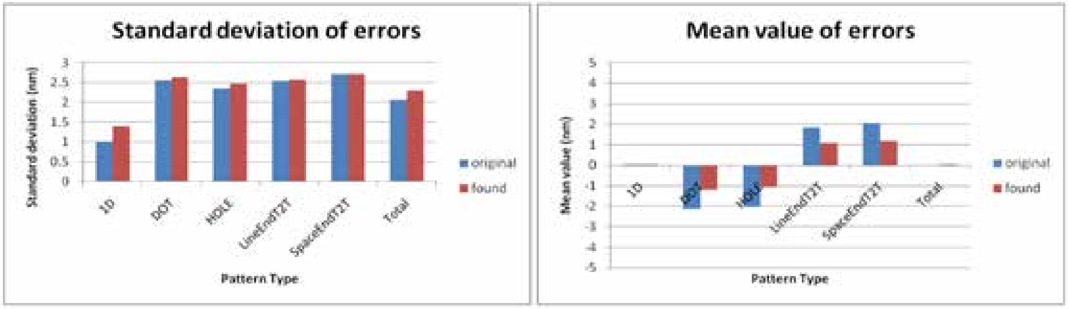

Figure 14. After modeling with data which has mixed dispersion and shift errors, standard deviations and mean values are compared between original errors and found errors. Model is calibrated such that average of total errors is 0 and standard deviation of those is minimized. That causes model distortion when there are shift errors by each type of patterns.

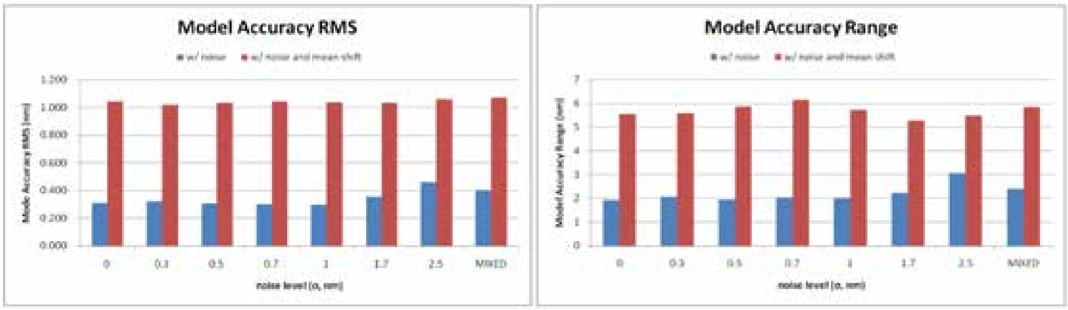

Figure 15. Model accuracy with noise and mean shift.

Industry Briefs

5nm Test Lights Litho Path: Hybrid 193i, EUV Seen as Best Approach

Rick Merritt, EETimes, 10/7/2015

SAN JOSE, Calif. – Two 5nm test chips pushed to their limits today's 193-immersion and future extreme ultraviolet lithography. They confirm using a mix of 193i and EUV techniques likely is the best approach as the industry drives toward the limits of Moore's Law.

The Imec research institute in Belgium and Cadence Design Systems partnered on the test chips that involved SRAM and placed-and-routed processor cores. The chips were made with line pitches as small as 24nm, close to the theoretical limit of a quad-patterned immersion process. Three approaches were tested to make the chips – using all 193i steppers, using all EUV and using a mix of 193i and EUV systems.

The 193i-only approach was potentially the most expensive, requiring quad patterning for metal layers and triple patterning for vias. The all-EUV approach needed fewer layers and supported better area, power and performance but was not practical given the still immature state of EUV systems. In the hybrid approach, 24nm metal lines required four passes through 193i steppers using a Self-Aligned Quadruple Patterning (SAQP) technique and vias with a single pass through EUV. However, at a metal pitch of 24nm, the cut distance starts to be close to the EUV single-exposure limit, so one would start to need two EUV passes, according to Praveen Raghavan, a principal engineer at Imec.

eBeam Initiative Survey Shows Rising Optimism in EUV Lithography

Solid State Technology, 29/9/2015

The eBeam Initiative, a forum dedicated to the education and promotion of new semiconductor manufacturing approaches based on electron beam (eBeam) technologies, today announced the completion of its fourth annual eBeam Initiative members' perceptions survey. A record 64 industry luminaries representing 35 different companies from across the semiconductor ecosystem–including chip design, equipment, materials, and manufacturing, as well as photomasks–participated in this year's survey.

The respondents expressed increased optimism in the implementation of EUV lithography for semiconductor high-volume manufacturing (HVM) compared to last year's survey, while at the same time acknowledging that EUV lithography is expected to add greater complexity to photomask manufacturing. In addition, expectations on the use of multi-beam technology continue to remain strong.

- 62% of respondents predict that multi-beam technology will begin to be used for photomask production by the end of 2016 to address the mask write times as the industry moves to smaller geometries.
- Mask makers appear to be the most optimistic about the availability of multi-beam mask writers. 96% of them indicated that multi-beam will be used for HVM mask writing by the end of 2018, compared to 65% of the equipment suppliers.
- Among five next-generation lithography (NGL) technologies considered for advanced semiconductor fabrication, respondents predict EUV as the most likely NGL method to be used in at least one manufacturing step by 2020, with an average confidence rating of 62%.
- At the same time, 59% of respondents predict that EUV will drive the need for complex mask shapes.
- Mask sets below the 22-nm logic node are exceeding 60 masks for the first time, while mask sets have seen a long-term growth rate of 13% since the 250-nm node.
- Average mask writes times have exceeded the nine-hour mark (9.6 hours) while the longest write time reported was 72 hours.
- A strong majority (75%) of mask makers predict that they will modulate exposure dose on a per-shot basis in 2017.

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