Study of EUV stochastic defect on wafer yield

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ABSTRACT

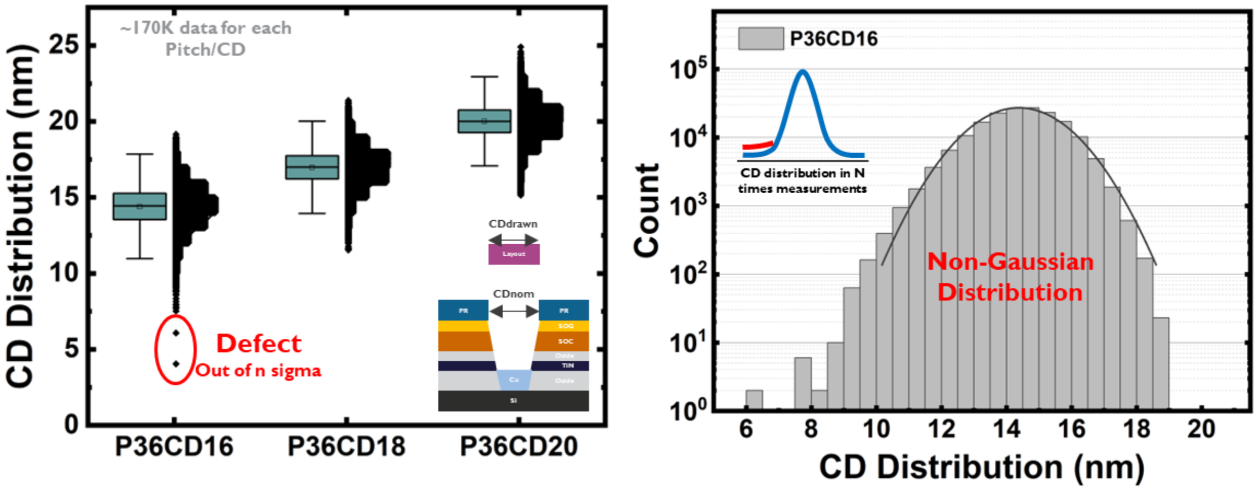
As semiconductor industry transitions to EUV lithography in advanced technology nodes, EUV stochastic defects play a significant role in chip yield degradation. Present yield models do not account for the stochastic-driven defects that changes by both pitches and critical dimensions (CD) in EUV lithography. In this study, a novel approach that incorporates EUV stochastics into the yield modeling, using calibrated stochastic defects from wafer data is introduced. Then a comparative analysis of yield for various EUV insertion scenarios is meticulously performed. Additionally, strategies to enhance yield in EUV lithography, including CD retargeting are proposed.

Keywords: EUV Stochastic, defect density, yield model, defectivity, Stochastic failure, manufacturability

1. INTRODUCTION

As the semiconductor industry progresses, there is a notable shift towards adopting Extreme Ultraviolet (EUV) lithography as the primary technology in the production of semiconductor devices, especially in advanced technology nodes. EUV lithography is a cutting-edge lithography technique that utilizes extremely short wavelengths of light, allowing for more precise printing of the critical features on wafer. This transition to EUV lithography in advanced technology nodes signifies a move towards more advanced and challenged processes in the semiconductor manufacturing industry [1].

As EUV lithography is inserted into the production process, there could be some unpredictable variations. It is well known that stochastics can cause variations in printing patterns. Hence, it's believed that EUV Stochastic effects can lead to higher failure probability. Figure 1 (a) shows the CD distribution in different CDs for Pitch of 36nm. When the feature size becomes smaller and smaller, there are more defects that could be found out of certain sigma [2]. Figure 1 (b) further illustrates the CD distribution of Pitch of 36nm and CD of 16nm. When it comes to smaller CD, we can find that the Gaussian distribution starts to have a tail and becomes asymmetric towards the smaller CDs. Stochastics can describe some random variables.



(a) (b)

Figure 1 (a) suggests more defects are found with small CD due to EUV stochastics. (b) illustrates CD distribution of P36CD16, showing Gaussian distribution with a tail on the smaller CD side.

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In this study, we consider stochastic defects in reality as the dimensions scale. In addition, with stochastic, defect density varies with Pitch and CD. We consider stochastic effect into our previous yield model [3][4]. Thus, the yield model has been improved in this study. To achieve better yield, we propose a strategy which is retargeting CD to reduce defect density. In the future, by optimizing exposure conditions such as dose, exposure time and focus, it can also help to enhance yield in semiconductor industry.

2. METHODOLOGY – DEFECT DENSITY CONVERSION

In this section, first, we compare the program flow of the conventional yield model and the proposed yield model, considering wafer-data-calibrated defect density. Then, with the Stochastic Compact Model (STCM), the methodology of defect density conversion is further introduced.

2.1 Comparison of conventional yield model and proposed yield model

In the conventional yield model, we use the constant defect density for all the patterned layers. In this proposed yield model, we consider stochastic effect, then with the wafer data calibrated model, we can get the failure number to convert to defect density. By comparing the output of the defectivity simulation using calibrated model and the wafer data from the defect inspection tool, it can further improve the accuracy of the stochastic defects model. With the more accurate model, wafer data defectivity can be updated. Therefore, we not only take into account the stochastic effect and embed the latent defects induced by Stochastic (STC) within the formula parameters, but also combine wafer calibrated data into the yield model, as illustrated in Figure 2.

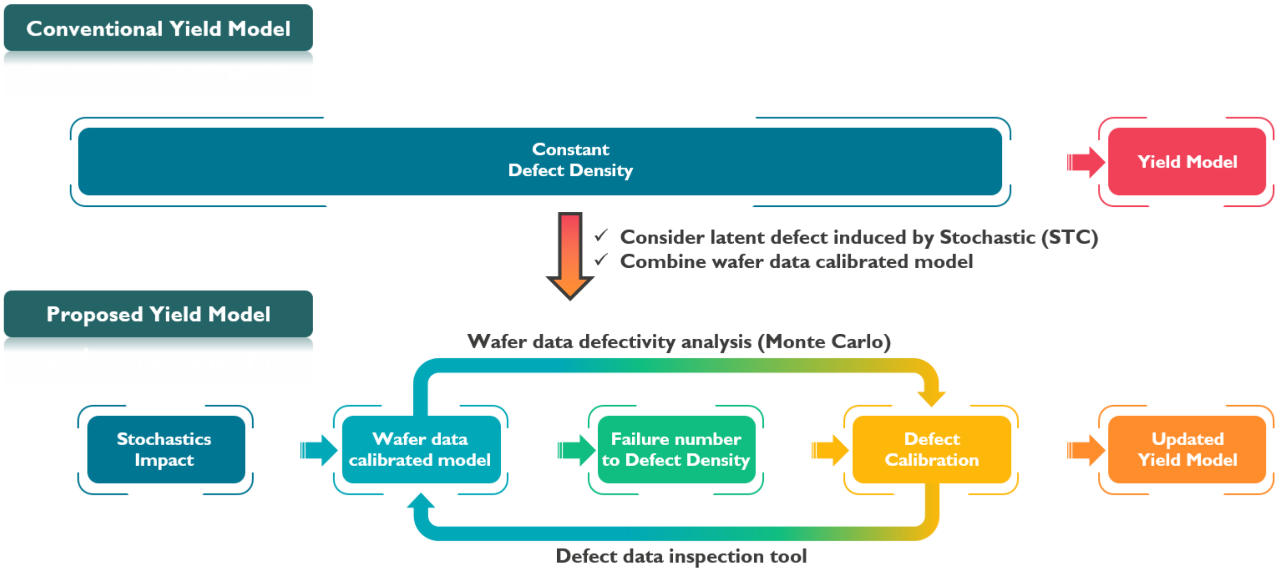


Figure 2. The yield model proposed in this study takes the stochastic effect into account and combines a wafer data-calibrated model with the yield model.

2.2 Methodology by Stochastic Compact Model (STCM)

The methodology by Stochastic Compact Model (STCM) is based on Calibre nmModelflow [5]. In this model, users can specify the pixel size, the number of inspected pixels, and subsequently, the count of failed pixels (pixels that contain defects). As shown in Figure 3, for instance, with commands “num_pix = 10” and “num_fail = 1”, signifying 10 gauges to inspect, if the tool identifies a gauge as either nonexistent or smaller than the specified pixel size, it is marked as 'failed,' resulting in Pix_NOK being equal to 1.

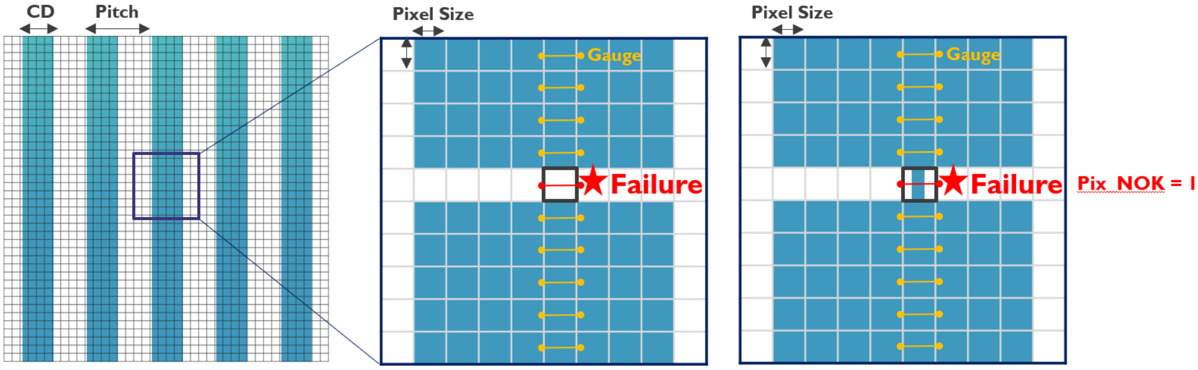


Figure 3. The methodology by stochastic compact model is based on pixel-based modeling tool.

This simulation tool is calibrated with wafer data. With the simulation tool, we can convert the number of the failures, denoted as “Pix_NOK” to defect density.

$$Pix\_NOK \equiv \#Failure\ in\ N\ iterations$$

By considering the number of failures and the inspection area, the defect density can be calculated. The inspection area includes pixel size, number of pixel to detect in one measuremnet, and the pitch of the simulation pattern as illustrated in Figure 4. The total inspection area also takes acount the number of simulation iterations.

The defect density conversion formula is presented below.

$$Defect\ density \equiv \frac{Pix\_NOK}{N\ \ iterations \times Inspect\ cell\ size}$$

With the inclusion of the inspection area, the formula can be modified as follows.

$$Defect\ density \equiv \frac{Pix\_NOK}{N\ \ iterations\ \times (pixel\ size \times num\_pix\ \times Pitch)}$$

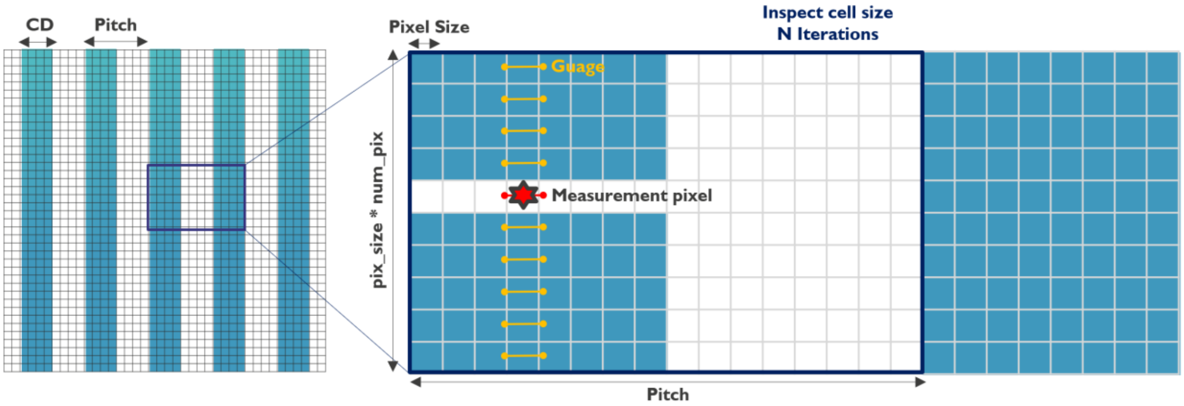


Figure 4. Convert number of failures to Defect density (unit: cm^{-2}) by taking into account the inspection area.

Hence, with the calibrated model, the stochastic defects probability can be simulated and further converted into defect density. This calibrated simulation result can then be incorporated into the proposed yield model with the Stochastic Compact Model (STCM), presenting a more accurate yield model and corresponding results.

3. RESULT – EUV STOCHASTIC DEFECT DENSITY FOR YIELD MODEL

In this section, the defect density with STCM for different pitches is shown in 3.1. Then, a comparison of the yield model with and without STCM, applied to two cases— one representing a single BEOL level and the other involving EUV nodes— is presented with this updated yield model.

3.1 Defect density with STCM for Different Pitches

Figure 5 shows the EUV defect density resulting from EUV direct printing at various pitches— P39, P36, and P32, with each point representing the pitch and its CD equal to half-pitch. This EUV defect density is benchmarked to Deep Ultraviolet (DUV) specifications defined in our previous studies [3][4]. It reveals that a higher defect density is observed in smaller pitches, indicating the impact of the stochastic effect.

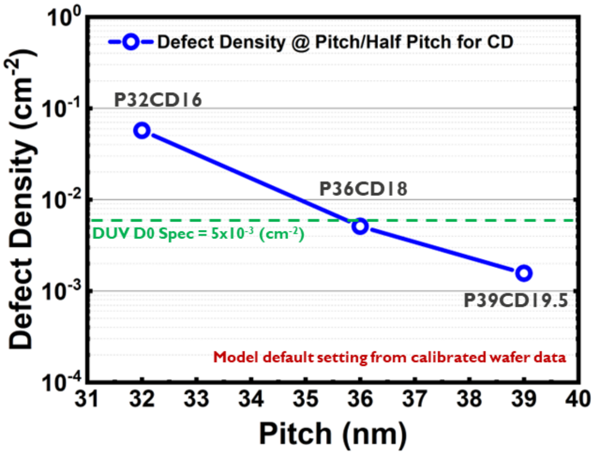


Figure 5 EUV defect density for P39, P36, P32 in EUV direct printing reveals higher defect density is observed in smaller pitches/CD.

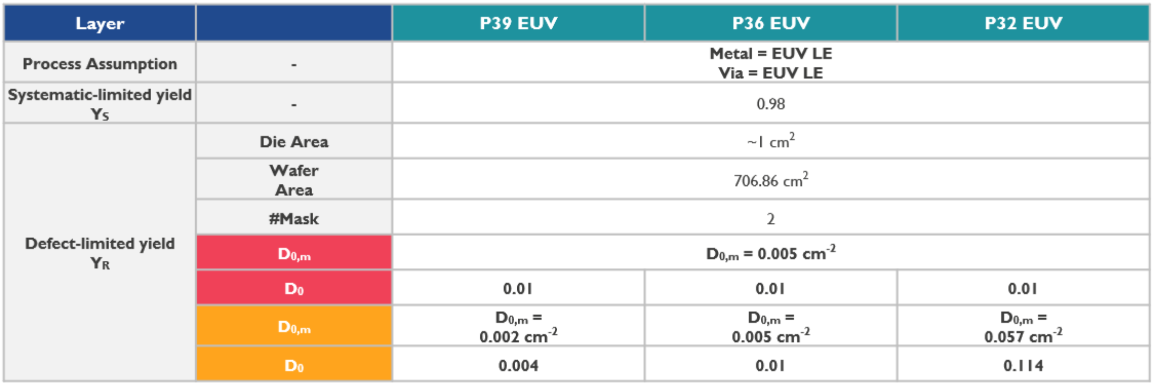
3.2 Comparison of Yield Model w/ and w/o STCM

The yield model comprises two parameters: Systematic-limited yield (Y_S) and Random yield loss (Y_R), the latter being associated with latent defects and consequently referred to as defect-limited yield. Further details on Yield Model parameters can be found in previous works [3][4]. In this study, Poisson model will be used.

The formula for wafer yield with Random yield loss (Y_R), according to the Poisson Model, is presented as follows.

$$Wafer\ yield = Y_S \times Y_R = Y_S \times e^{-AD_0} = Y_S \times e^{-AD_{0,m} \times \#mask}$$

The parameters defect density (D_0) and mean defect density ($D_{0,m}$) exhibit variability as a consequence of stochastic effects within the yield model incorporating EUV Stochastic Compact Model (STCM).



Layer		P39 EUV	P36 EUV	P32 EUV
Process Assumption	-	Metal = EUV LE Via = EUV LE		
Systematic-limited yield Y_S	-	0.98		
Defect-limited yield Y_R	Die Area	~1 cm^2		
	Wafer Area	706.86 cm^2		
	#Mask	2		
	$D_{0,m}$	$D_{0,m}$ = 0.005 cm^{-2}		
	D_0	0.01	0.01	0.01
	$D_{0,m}$	$D_{0,m}$ = 0.002 cm^{-2}	$D_{0,m}$ = 0.005 cm^{-2}	$D_{0,m}$ = 0.057 cm^{-2}
	D_0	0.004	0.01	0.114

Table 1. Mean defect density ($D_{0,m}$) and defect density (D_0) are varied in the proposed yield model with STCM

In the conventional yield model, stochastic effects are not considered, leading to a constant mean defect density value. Hence, when the defect density is identical, the predicted yield remains constant, leading to weaker yield predictions. In contrast, the proposed yield model, as illustrated in Figure 6, takes into account stochastic effects, causing the mean defect density ($D_{0,m}$) to vary across different pitches, consequently resulting in different total defect density (D_0). As a consequence, the yield model becomes more reliable as it is influenced by varying defect density levels at different pitches.

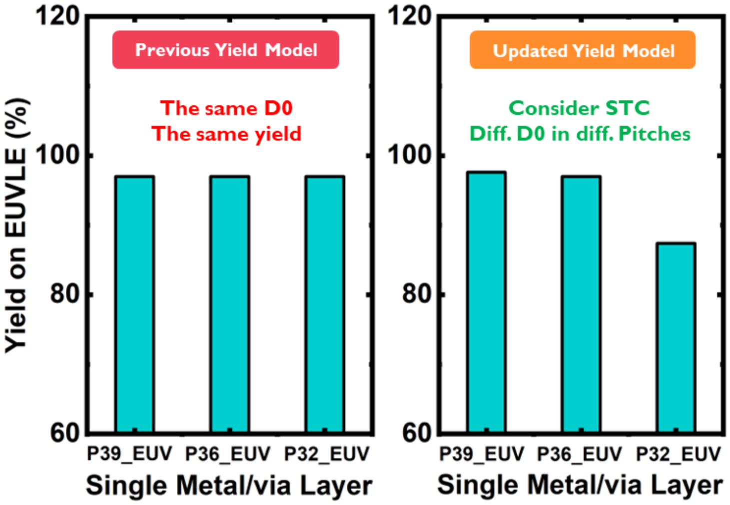


Figure 6 The proposed yield model is more reliable as it is influenced by varying defect density levels at different pitches, resulting in more realistic yield result.

3.3 Yield w/ STCM in Single BEOL Level

Two cases of patterning process assumptions are applied to the yield model with Stochastic effect, showing the results influenced by Stochastic effects. The first case involves process assumptions for a single BEOL level, encompassing one metal and one via, as illustrated in Figure 7. This figure shows the patterning process assumption for different pitches and for different lithography options (193i and EUV) as well as the number of masks needed for each of these options.

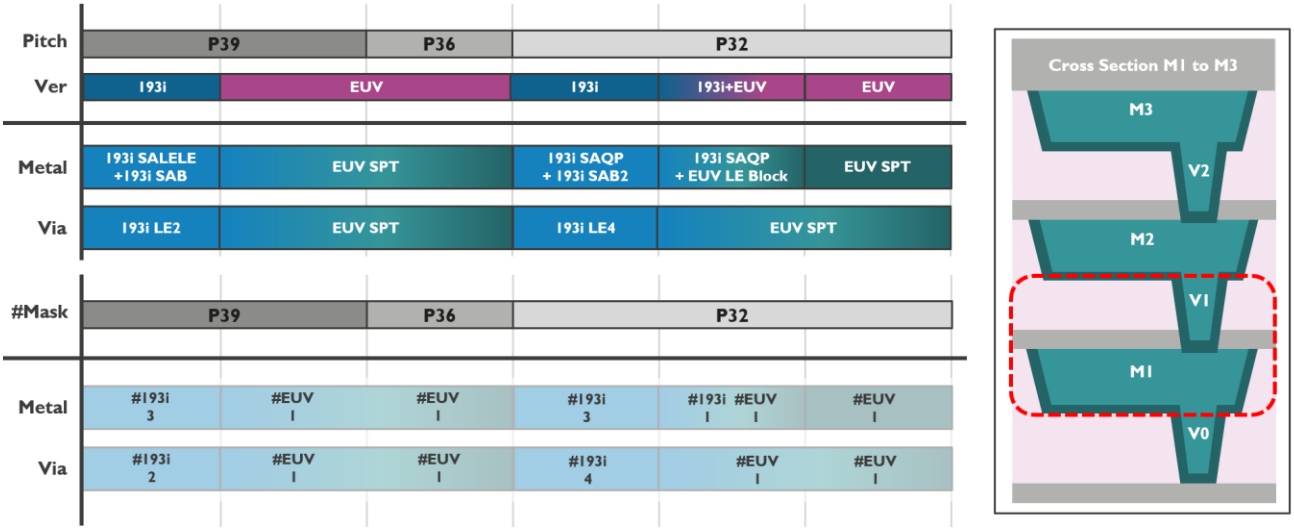
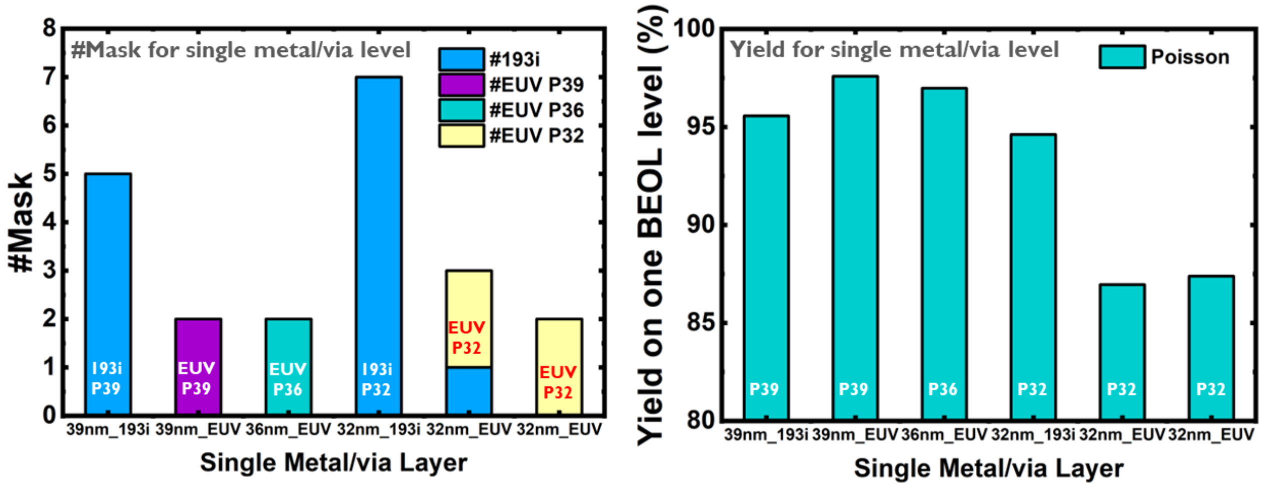


Figure 7 The patterning process assumption and the corresponding number of masks needed for single BEOL level (M1-V1)

Figure 8 (a) illustrates the total number of masks needed at different pitches and various patterning options, while Figure 8 (b) presents the corresponding yield results. Comparing the 193i to the EUV options at P39 reveals that EUV insertion can help to decrease the number of masks, resulting in an improved yield. For pitches from P36 to P32, considering EUV single patterning option, the number of masks remains constant; however, the yield drops dramatically, indicating a significant impact of the stochastic effect on the yield. Even at P32, where EUV insertion reduces the number of masks, the higher defect density in P32 due to the stochastic effect still results in a decline in yield for the EUV option.



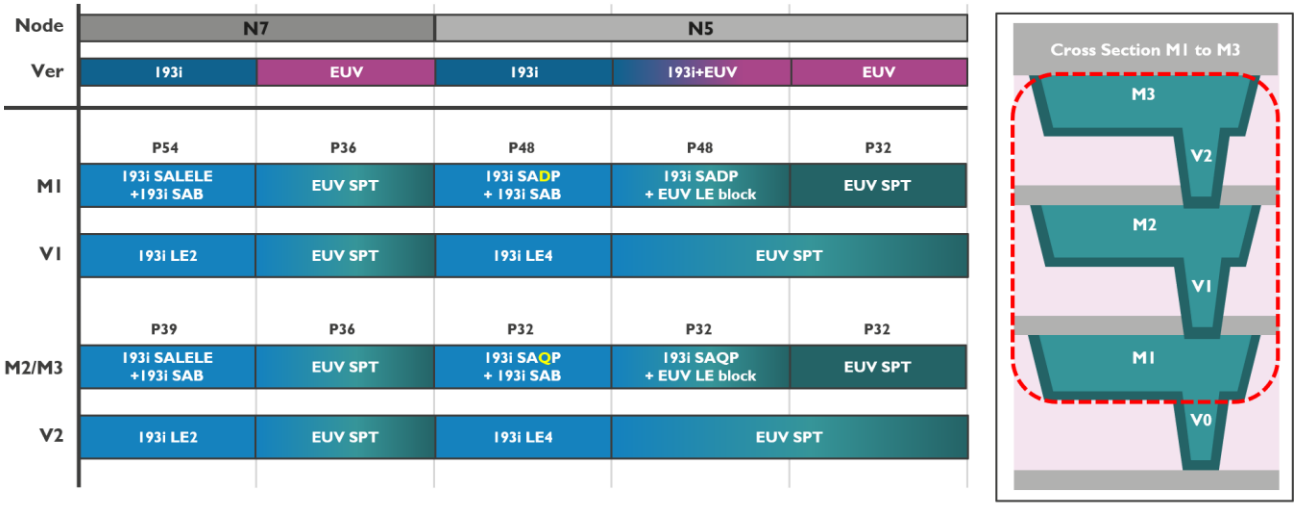
(a)

(b)

Figure 8 (a) illustrates the number of masks, while Figure 8 (b) presents the corresponding yield results for different pitches and lithography options in a single metal/via layer level.

3.4 Yield w/ STCM in EUV Nodes BEOL level

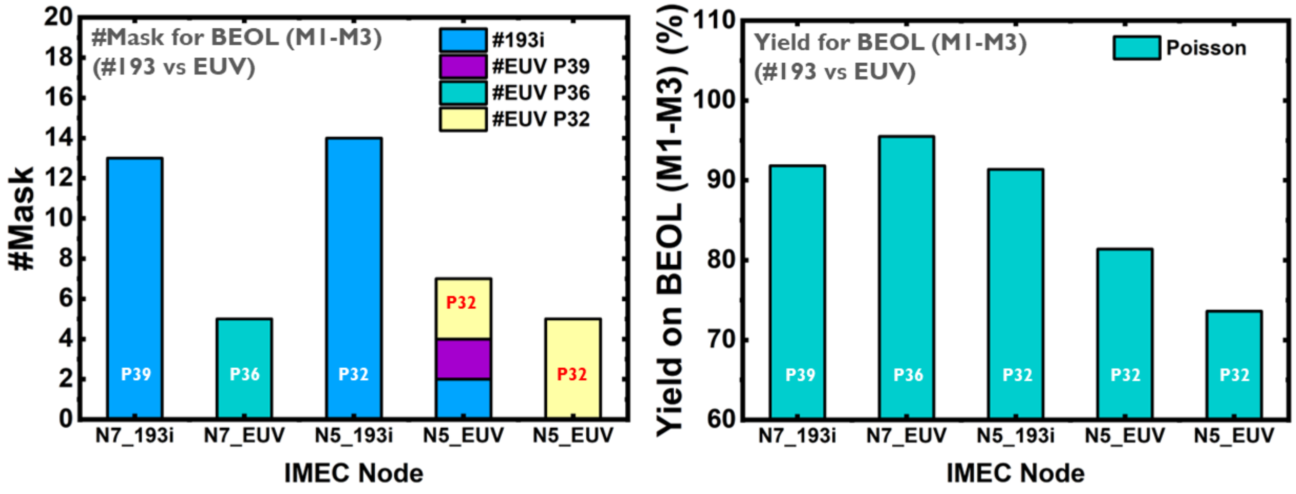
Furthermore, the patterning process assumptions for N7 and N5 imec logic nodes, incorporating various patterning options, are applied to the yield model with stochastic effect taken into account. This study focuses on the yield of Back-End-of-Line (BEOL) from M1 to M3. N7 EUV option employs P36, while N5 starts to insert P32 for both 193i and EUV options. In the updated yield model, different defect densities are applied to different pitches. The yield can be calculated based on the corresponding number of masks.



Node	N7		N5		
Ver	193i	EUV	193i	193i+EUV	EUV
	P54	P36	P48	P48	P32
M1	193i SALELE +193i SAB	EUV SPT	193i SADP + 193i SAB	193i SADP + EUV LE block	EUV SPT
V1	193i LE2	EUV SPT	193i LE4	EUV SPT	
	P39	P36	P32	P32	P32
M2/M3	193i SALELE +193i SAB	EUV SPT	193i SAQP + 193i SAB	193i SAQP + EUV LE block	EUV SPT
V2	193i LE2	EUV SPT	193i LE4	EUV SPT	

Figure 9 The patterning process assumption for EUV and 193i nodes (N7-N5)

In Figure 10, firstly, for N7, from 193i to EUV options shows that EUV insertion reduces the number of masks and improves the yield. Additionally, going from N7 EUV to N5 193i increases the number of masks, resulting in a decrease in yield. With smaller Pitch/CD, such as P32 in this case, stochastic effects significantly impact the yield and should be considered. Subsequently, in N5 P32 with EUV stochastic, although the number of masks can be reduced using EUV compared to the 193i, the yield still drops due to the higher defect density caused by the stochastic effect.

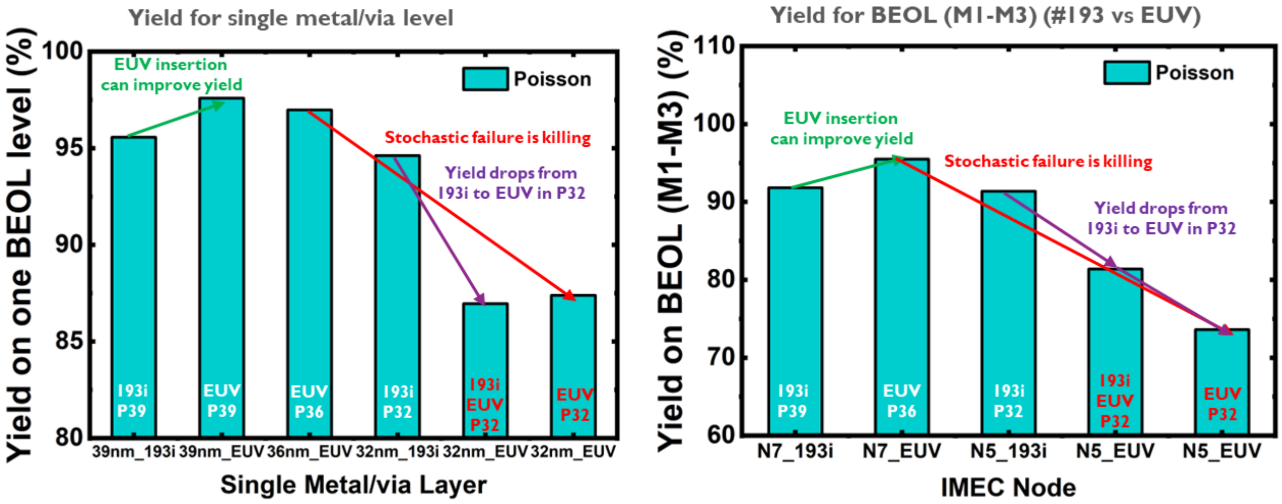


(a) (b)

Figure 10 (a) illustrates the number of masks and (b) presents the corresponding yield results for different nodes in different patterning options (EUV vs. 193i).

3.5 Summary for Stochastic Failure

First, in BEOL single metal level, as shown in Figure 11(a), reveals the influence of stochastic effects on yield at various pitches and patterning options. EUV insertion at P39 reduces mask count, enhancing yield, while at P32, despite reduced number of masks, stochastic effects lead to a decline in yield. Second, in BEOL levels M1-M3, presented in Figure 11(b), we have demonstrated the impact of EUV insertion on mask count and yield for N7 and N5 nodes. The study emphasizes that stochastic effects significantly impact yield, evident in both cases. It's important to consider stochastic effects, particularly in smaller Pitch scenarios such as P32, in advanced semiconductor yield modeling.

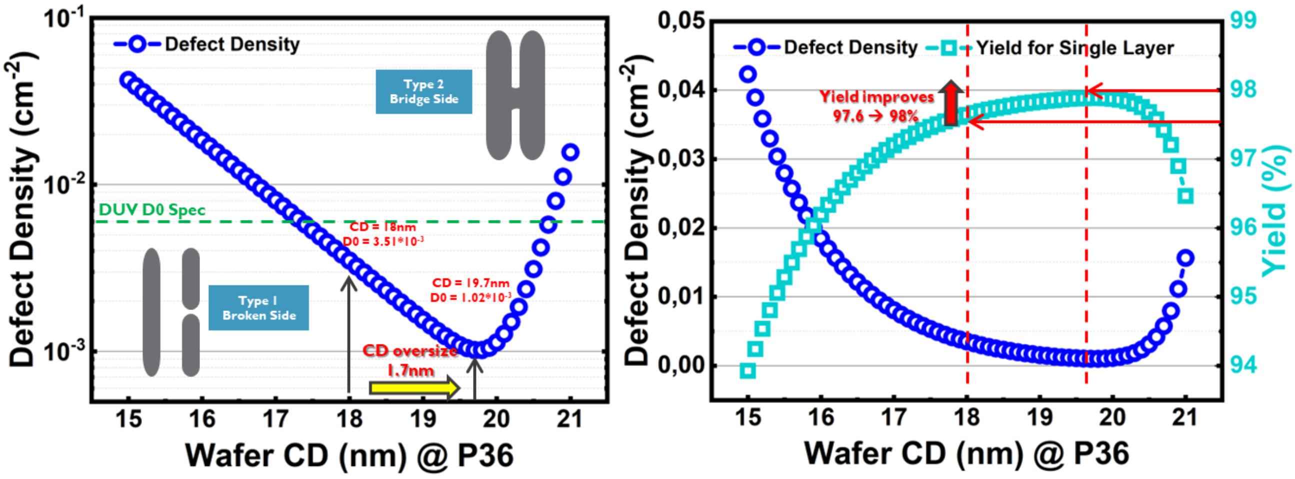


(a) (b)

Figure 11. The yield on (a) one BEOL level and (b) yield for N7 and N5 nodes BEOL level (M1-M3).

4. PROPOSAL – DEFECTIVITY IMPROVEMENT

Finally, we propose a strategy to mitigate defectivity. Figure 12 (a) depicts defect density across different wafer critical dimensions (CD) at P36, revealing two defect types: 'Broken' for smaller CDs and 'Bridge' for larger CDs. Consequently, defect density increases on both sides, with the minimum observed at CD = 19.7 nm, rather than CD that is equal to half-pitch. This suggests a potential 3.5 times reduction in defect density with a 1.7 nm oversizing of the CD. In Figure 12 (b), defect density is presented on a linear scale, showing its correlation with yield. Thus, oversizing proves effective not only in reducing defect density but also in improving yield.



(a) (b)

Figure 12 (a)(b) illustrate the impact of retargeting strategies, demonstrating CD oversizing contributes to achieving improved yield.

5. CONCLUSION

In conclusion, this study presents the significance of incorporating a stochastic model in real-world scenarios, emphasizing its importance as dimensions scale and its impact on defect density. The enhancement of the wafer yield model is successfully achieved by considering the stochastic effect, resulting in variable defect density with changes in Pitch and the CD. This updated yield model with stochastic effects lays the foundation for a proposed strategy to enhance yield performance. Through CD retargeting, the reduction of defect density is proposed to improve overall yield results.

REFERENCES

[1] Harry Levinson, Timothy Brunner, "Current challenges and opportunities for EUV lithography," SPIE Photomask Technology and Extreme Ultraviolet Lithography, 2018, Monterey, California, United States. Proceedings Vol. 10809, International Conference on Extreme Ultraviolet Lithography. DOI 10.1117/12.2502791

[2] Toru Fujimori, "Recent status of the stochastic issues of photoresist materials in EUV lithography," SPIE Photomask Technology and EUV Lithography, 2022, Monterey, California, United States. Proceedings Vol. 12292, International Conference on Extreme Ultraviolet Lithography. DOI 10.1117/12.2643036

[3] Yi-Pei Tsai, et al., "A yield prediction model and cost of ownership for productivity enhancement beyond imec 5nm technology node," SPIE Advanced Lithography and Patterning, 2022, San Jose, California, United States. Proceedings Vol. 12052, DTCO and Computational Patterning. DOI 10.1117/12.2617415

[4] Yi-Pei Tsai, et al., "Productivity enhancement study; Yield, cost and turn-around-time modeling for EUV and high NA EUV," SPIE Advanced Lithography and Patterning, 2023, San Jose, California, United States. Proceedings Vol. 12495, DTCO and Computational Patterning. DOI 10.1117/12.2658866

[5] Chih-I Wei, et al., "Calibration and application of Gaussian random field models for exposure and resist stochastic in EUV lithography," in Japanese Journal of Applied Physics (JJAP), vol. 61, no. SD0806, May. 2022. DOI 10.35848/1347-4065/ac54f5