Reduction in Scattered Particles Contamination in Inductively Coupled Plasma Etching Systems for High Volume High Yield Production

Mohammadsadegh Beheshti, Samuel Mony, Nercy Ebrahimi, Tom Brown

Skyworks Solutions, Inc., 2427 West Hillcrest Drive, Newbury Park, CA 91320
e-mail: Mohammadsadegh.Beheshti@skyworksinc.com Phone: +1 (805) 285-8091

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Abstract

A significant challenge in high volume semiconductor manufacturing is reduction of particle defects. This study concentrates on plasma etch processes using an Inductively Coupled Plasma (ICP) tool. Particles in an ICP etch tool originate from the etchant gases and etch byproducts that deposit on the chamber components and tend to fall on the wafer during etch. In this paper, a new clean and conditioning procedure to reduce particle formation in a chlorine-based process is reviewed. Automated Optical Inspection (AOI) of the wafer before and after the etch, help to quantify the yield improvement. Implementation of clean and conditioning before every production lot, reduced the yield loss from ~6% to ~1.5% at highest RF hours of the chamber. Average of individual defects with highest population dropped from ~30 to ~5 per wafer. Eliminating a strong correlation between yield drop versus the number of particles of the same size was shown by regression as a character of clean. Classification revealed another character of the clean with reducing the probability of wafers to fail from ~80% down to ~50% for a same particle numbers and size. More advanced classification based boosting model conveyed another physical property of this clean in eliminating the influence of certain particle sizes on the yield loss.

INTRODUCTION

Plasma based dry etch is commonly used in semiconductor device fabrication. One of the major contributors to defect formation on wafers in plasma etch is particulate contamination [1-3]. Particles can either block the etch or remain on the wafer after the etch causing overall yield loss [4]. Generation of particles in the etch chamber, is affected by the etchant gases and the materials being etched and condition of the chamber [5]. These defects may originate from chamber walls, lid, gas inlet, electrostatic chuck, plasma or wafer itself. To suppress the particle generation, techniques such as dehydration of chamber walls [6] and protective coating [7] were used. Inductively coupled plasma (ICP) based cleaning techniques have been reported in tools that run production with fluorine-based gases [8-9].
Automated optical inspection (AOI) is commonly used to extract the particle defects maps and images data including defects area, dimension, aspect ratio and coordination on the wafer [10]. The overall statistical data contains the critical leads to discover sources of the defects and determining which source controls the generation of what type of defects [11]. For example, simulation models for defects categorized into their pattern types provides information about causes including particles, chemical stains, or human mistakes. Costly, erroneous and insufficient process of manual analysis of the data drive the analysis processes toward using machine learning models [12].
This paper introduces a new technique to add a clean and conditioning procedure in ICP tools running high volume production with a chlorine-based gas to remove sources of particles. The chemical sources of defects were investigated by analyzing the elemental composition of the defect. AOI results of wafers before and after etching in the ICP tool was used to demonstrate the effectiveness of adding the clean process in reducing added particles during etch. The AOI yield drop during etch with and without clean were compared. Distribution of the average number of particles added to the wafers during the etch versus the particle size was shown for each condition. The yield values versus the number of particles sorted by size, were documented for all conditions. Supervised machine learning models were fitted to the data for each of the conditions with and without clean. Regression and classification models were created to identify the correlation and estimate the yield drops versus the number of the particles of a certain size. Gradient boosting model was used to determine the significance of particle numbers in controlling the yield drops for each particle size. The results of these models were used to explain the physics of adding the clean to the process based on the results. They can also be used for future studies to determine the most effective particles reduction solution among cleans with different gas chemistries, plasma conditions or non-plasma-based approaches.

EXPERIMENTAL

Production wafers processed in two ICP tools were used to perform the experiments. MOCVD grown six-inch GaAs wafers were processed through several integration steps and were etched at different layers in these two tools. AOI tool was used to inspect wafer surface before and after the etch step. Inspection results were used to calculate the yield drops and defects added to the wafers solely during the etch in two conditions: with clean and without clean. Seven lots were with no clean and seventeen lots with added clean were inspected before and after the etch. Bare GaAs wafers used for clean and conditioning before running the lot. An Oxygen based clean with high pressure together with a chlorine-based conditioning both with high ICP to bias power ratio above 20:1 was used for the clean and conditioning.

RESULTS AND DISCUSSION

Fig. 1 shows the AOI wafer map before and after etch, with no clean, showing the defects as small dots. The insets show the scanning electron microscope (SEM) and energy dispersive spectroscopy (EDS) of the same particle added to the wafer during the etch. The number of particles normally added to the wafer during the etch were quite significant, causing ~2.3% yield loss for this wafer.

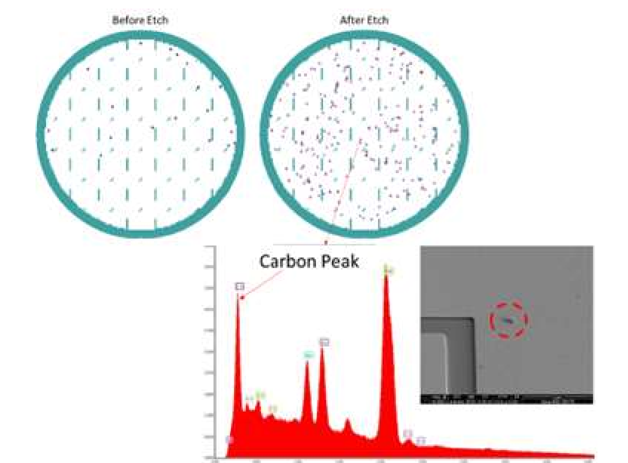

Fig. 1. AOI wafer map before and after etch with no clean. The insets show the SEM and EDS data of an added particle during etch.

The results of a sample wafer AOI map of the defects before and after the etch with added clean were shown in Fig. 2. From the defect map, the number of the particles added to the wafer during the etch was significantly reduced to ~0.2% compared to the wafer shown in Fig. 1.

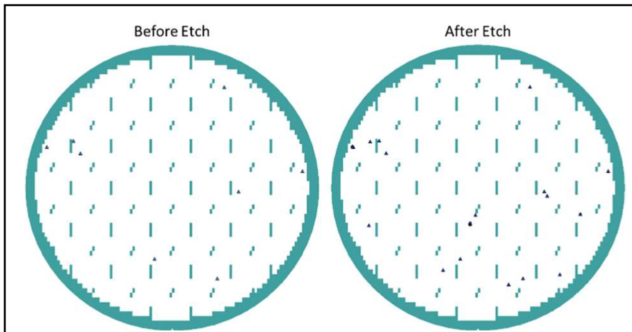

Fig. 2. AOI wafer map before and after etch with the clean implemented before running the production lot.

To compare the overall effects of implementing clean before running the production lots, the yield drops were plotted as a function of tool RF hours in Fig. 3. No clean before running lots plotted in red results in relatively higher yield drop compared to implementing clean before every lot plotted in blue. We can see that the added defects increase significantly when no clean is used in the process.

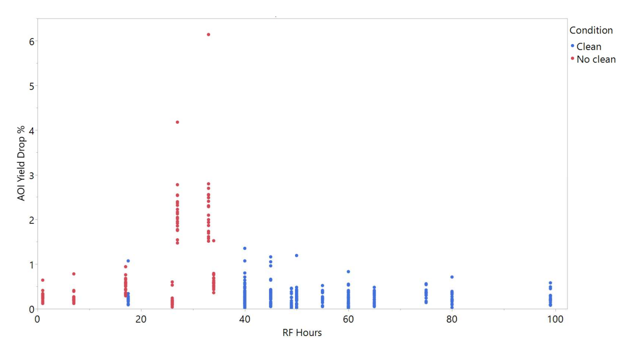

Fig. 3. AOI yield drop percentage per tool RF hours.

In Fig. 4 we have plotted the average number of particles added to the wafers sorted by particle size for both no clean (a) and with clean (b) conditions. The insets in each condition shows the first seven particle sizes with the highest average values. Interestingly, for both conditions, the particle size with the highest number of added particles during the etch is the same 2um. It should be noted that typically larger size particles have much fewer adders. With the clean process the average number of added particles for all sizes were reduced showing the overall effectiveness of implementing the clean.

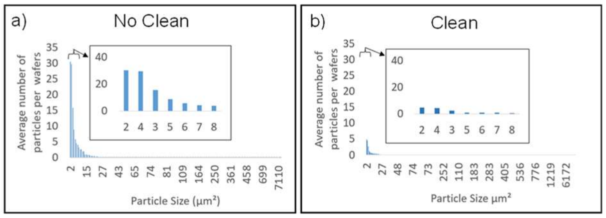

Fig. 4. Average distribution of the particles per wafer for each particle size when a) no clean, b) clean was applied.

To underline the effectiveness of adding a clean process, a polynomial regression model for 2 µm² particles was generated, shown in Fig. 5. The solid lines show the fitted model, and the dashed lines show the estimated 95% confidence intervals for the function. In the no clean model, the yield drop is a stronger function of number of particles compared to clean condition. A second-degree polynomial could better describe the no clean yield drop whereas the yield drop in the clean is a weak linear function of the number of 2 µm² particles. Even excluding few higher points for no clean, a first degree polynomial would have a higher slope for no clean compared to clean. This indicates that the clean mitigated the effect of the number of 2 µm² particles on the yield drop during the etch. For estimation purpose, at high number of particles in clean, we don't expect much increase in yield loss as opposed to no clean. This regression model can be produced for other particle sizes and be used to determine the effectiveness of adding the clean in controlling other sizes of particles based on the yield losses achieved.

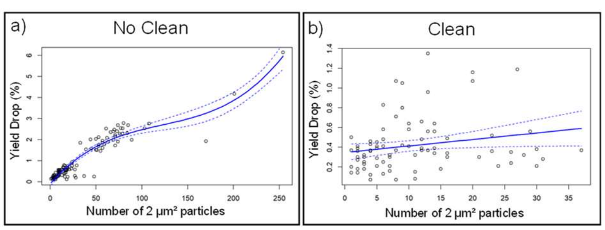

Fig. 5. Regression models for yield drop per the 2 µm² particles when a) no clean, b) clean was applied.

The regression model for each particle size explained in Fig. 5, could be transformed into a classification model for simplifying the model and presenting in terms of "pass" and "fail" used in yield engineering. The classification model can provide more meaningful estimation especially at high number of particles of each size based on the physical conditions of the process. In this model, a yield drop of greater than 0.5% could be determined as fail for each of the processes, therefore a probability number 1 shows the yield drop being greater than 0.5 and the yield drop being smaller or equal to 0.5 shows a probability number of 1. Fig. 6. shows this model as a function of the number of 2 µm² particles. The solid lines in Fig. 6 show the fitted yield drop probability function and the dashed lines show the estimated 95% confidence intervals for the probability. The probability function is a second-degree polynomial for the no clean whereas the function is a linear versus the number of particles for the clean. The vertical small lines at the 0 or 1 probabilities show where the data occur. The no clean probability function shows almost a 100% value when having 50 or higher number of 2 µm² particles which means most likely the yield drops are beyond 0.5% in this region. The graph also shows that beyond ~20 number of 2 µm² particle, the probability of having yields drops higher than 0.5% is high. On the other hand, for the clean, probability linear function is closer to zero across all range of number of 2 µm² particles meaning the low probability of having more than above 0.5% yield drop in this condition. Overall, the physical estimation provided by the classification model is that by adding the clean to the process for the similar number of particles ~35, the probability of wafers to fail is ~50% as compared to no clean for which this probability is beyond 80%.

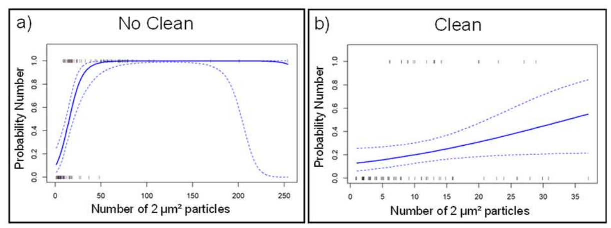

Fig. 6. Classification models for yield drop per the 2 µm² particles when a) no clean, b) clean was applied.

Extracting the influence of number of particles of various sizes on the yield drops allows determining the physical effects of adding the clean to the process in broader extent. Therefore, the classification approach was used to create a gradient boosting model to compare the effects of number of particles on yield drops for different sizes of particles up to 30 µm² shown in Fig. 7. In the absence of clean, particle sizes of 5 µm² and 7 µm² and in the presence of clean particle sizes of 2 µm² and 4 µm² play the most important role in controlling the yield loss. This can explain the natural physical character of this clean process which mitigates the influence particle sizes of 5 µm² and 7 µm².

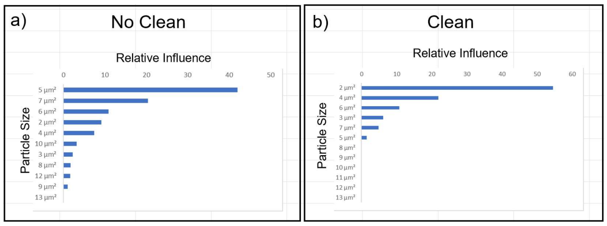

Fig. 7. Boosting models of the relative influence of yield drop per particles of different sizes when a) no clean, b) clean was applied.

CONCLUSIONS

This paper introduces a new clean and conditioning step in plasma ICP etch chambers before running the production lot to prevent particles from forming on wafers during etch process in high volume manufacturing. Defect particle detection AOI tool was used to inspect the wafers before and after the etch and determine the yield drop and particles added to the wafer only during the etch process. By implementing the clean and conditioning wafers, the yield drop was reduced significantly from the highest up to ~6% to less than ~1.5% even at the high RF hours of the ICP chamber. The average number of defects per wafer for the highest in pareto reduced from ~30 to ~5. Regression model for the smallest defect 2 μm^2 showed a strong relationship between the yield drop and number of particles in presence of clean showing that the clean reduced the effect of number of these particles on the yield drop. Classification model provided an estimation with high probability ~80% of wafers to fail in the absence as oppose to a probability of ~50% in the presence of clean for relatively small number of particles. Classification based boosting model revealed the physical character of the clean used here in reducing the influence of particle sizes of 5 μm^2 and ~7 μm^2 on yield drops. The results can be used for future studies to define the optimum clean process where the clean process nature or parameters vary.

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REFERENCES

[1] Ito, Natsuko, et al. "Observation of the trajectories of particles in process equipment by an in situ monitoring system using a laser light scattering method." Journal of Vacuum Science & Technology B: Microelectronics and Nanometer Structures Processing, Measurement, and Phenomena 16.6 (1998): 3339-3343.

[2] Jalali, Anahid, et al. "Predicting time-to-failure of plasma etching equipment using machine learning." 2019 IEEE International Conference on Prognostics and Health Management (ICPHM). IEEE, 2019.

[3] Hwang, Helen H., and Mark J. Kushner. "Regimes of particle trapping in inductively coupled plasma processing reactors." Applied physics letters 68.26 (1996): 3716-3718.

[4] UESUGI, Fumihiko, et al. "In-situ Monitoring of Particles Generated in Tungsten Etch-back Processing." Shinku 41.9 (1998): 776-781.

[5] Miwa, Kazuhiro, et al. "Particle reduction using Y2O3 material in an etching tool." 2007 International Symposium on Semiconductor Manufacturing. IEEE, 2007.

[6] Ito, Natsuko, et al. "Reduction of particle contamination in plasma-etching equipment by dehydration of chamber wall." Japanese journal of applied physics 47.5R (2008): 3630.

[7] Lin, Tzu-Ken, et al. "Comparison of erosion behavior and particle contamination in mass-production CF4/O2 plasma chambers using Y2O3 and YF3 protective coatings." Nanomaterials 7.7 (2017): 183.

[8] Ramos, R., et al. "Plasma/reactor walls interactions in advanced gate etching processes." Thin Solid Films 515.12 (2007): 4846-4852.

[9] Cunge, G., et al. "New chamber walls conditioning and cleaning strategies to improve the stability of plasma processes." Plasma Sources Science and Technology 14.3 (2005): 599.

[10] Abd Al Rahman, M., and Alireza Mousavi. "A review and analysis of automatic optical inspection and quality monitoring methods in electronics industry." Ieee Access 8 (2020): 183192-183271.

[11] Jiang, Dan, Weihua Lin, and Nagarajan Raghavan. "A novel framework for semiconductor manufacturing final test yield classification using machine learning techniques." Ieee Access 8 (2020): 197885-197895.

[12] Yuan, Tao, Suk Joo Bae, and Jong In Park. "Bayesian spatial defect pattern recognition in semiconductor fabrication using support vector clustering." The International Journal of Advanced Manufacturing Technology 51 (2010): 671-683.

ACRONYMS

AOI: Automated Optical Inspection
ICP: Inductively Coupled Plasma