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Splendidly blended: a machine learning set up for CDU control

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ABSTRACT

As the concepts of machine learning and artificial intelligence continue to grow in importance in the context of internet related applications it is still in its infancy when it comes to process control within the semiconductor industry. Especially the branch of mask manufacturing presents a challenge to the concepts of machine learning since the business process intrinsically induces pronounced product variability on the background of small plate numbers.

In this paper we present the architectural set up of a machine learning algorithm which successfully deals with the demands and pitfalls of mask manufacturing. A detailed motivation of this basic set up followed by an analysis of its statistical properties is given. The machine learning set up for mask manufacturing involves two learning steps: an initial step which identifies and classifies the basic global CD patterns of a process. These results form the basis for the extraction of an optimized training set via balanced sampling. A second learning step uses this training set to obtain the local as well as global CD relationships induced by the manufacturing process. Using two production motivated examples we show how this approach is flexible and powerful enough to deal with the exacting demands of mask manufacturing. In one example we show how dedicated covariates can be used in conjunction with increased spatial resolution of the CD map model in order to deal with pathological CD effects at the mask boundary. The other example shows how the model set up enables strategies for dealing tool specific CD signature differences. In this case the balanced sampling enables a process control scheme which allows usage of the full tool park within the specified tight tolerance budget.

Overall, this paper shows that the current rapid developments off the machine learning algorithms can be successfully used within the context of semiconductor manufacturing.

1. Introduction

The recent advances in machine learning have spurned numerous developments which already have a substantial impact on our daily lives. The most prominent examples can be found in the speech recognition software[1] as well as adaptive websites and recommender systems. As these

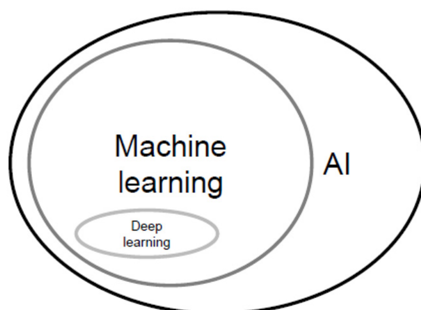

Figure 1. Machine learning is a subfield of artificial intelligence. Deep learning is a powerful technique within the field of machine learning.

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Editorial

"No Matter Where You Go; There You Are".

Thomas Struck, Infineon

With this quotation, Paul Ackmann concluded his presentation of the history of the "Integral Nature of Masks through five decades" at the 33rd European Mask and Lithography Conference (EMLC 2017), chaired by Uwe Behringer.

EMLC 2017 was held on June 27th -28th at the Hilton Hotel in Dresden. The big audience proved the relevance of EMLC even in the sluggish photomask business in Europe. Once again EMLC brought together more than one hundred and fifty scientists, researchers, engineers, and managers for extensive knowledge exchange about the latest developments in mask and lithography technologies and future strategies. Forty seven papers were presented within nine sessions over two and a half days. For the first time, technical tutorials were also offered, covering lithography and EUV.

During the conference, a technical exhibition helped provide a forum for discussion and networking within the community.

The welcome speech on "The Power of Power Semiconductors" was given by Mathias Kamolz from Infineon Technologies. Typically, the challenges for power products are not small feature sizes. Beside others, the processing of thin wafers (down to a 60µm thickness) is a major challenge especially for 300mm. Thanks to IoT, there is high demand for different applications and many different power chip designs. Note from the editor: High number of designs results in high demand for reticles and masks which benefits the mask making industry. In the 1st keynote ASML Jim Wiley gave an insight into "The status and challenges of the EUV photomask ecosystem". According to Jim, EUV is much more disrupting for the mask shop than for the wafer fab. The short-term EUV mask infrastructure challenges are: availability of actinic blank inspection, defect management without access to actinic patterned mask defect inspection, adequate supply of pellicles and low defect blanks, and the mask volume ramp itself. Long-term, EUV masks will be as routine as DUV masks are today. For 2017 Jim predicts a healthy mask eco system. As is normally done each year, best papers from BACUS 2016 and PMJ 2017 were also presented. In addition, Kurt Ronse from IMEC was invited to show the "Recent EUV developments at IMEC" which included a focus on bringing EUV "from lab to fab".

IMS and NuFlare showed their progress for the development of a multi beam mask writer. NuFlare recently shipped their first beta tool to target the market for 5nm node. IMS developed the MBM101. Based on a Jeol platform, several high volume manufacturing tools have been shipped ready for 7nm node. In conjunction with multi beam writing, processing and compressing of big data volume becomes important.

No surprise: Once more EMLC focused on the technology "race" between EUV and NIL. Therefore, multiple papers focused on these two candidates for next generation lithography. There is still a race ongoing, but different applications will probably allow the coexistence of both techniques in the long run. New aspects for a photo mask conference were considered in the session about the growing market for Non-IC application photomasks. Contrary to EUV, there is already a lot of revenue generated in the industry by Non-IC photomasks. That's why this topic is a "must have" of future conferences.

The topic of the final session was machine learning and its deployment to continuously improve the manufacturing process. Within this context "Splendidly blended: "A machine learning set up for CDU control" was honored as best paper. And it was a highlight from scientific and entertainment point of view.

"No matter where you go; there you are": This statement defines also the outlook for EUV which will be the next and last step in the optical train. In case you are wondering…this quotation comes from the eighties SiFi movie "Buckaroo Banzai".

Hope to see you at the next EMLC 2018 in Grenoble!

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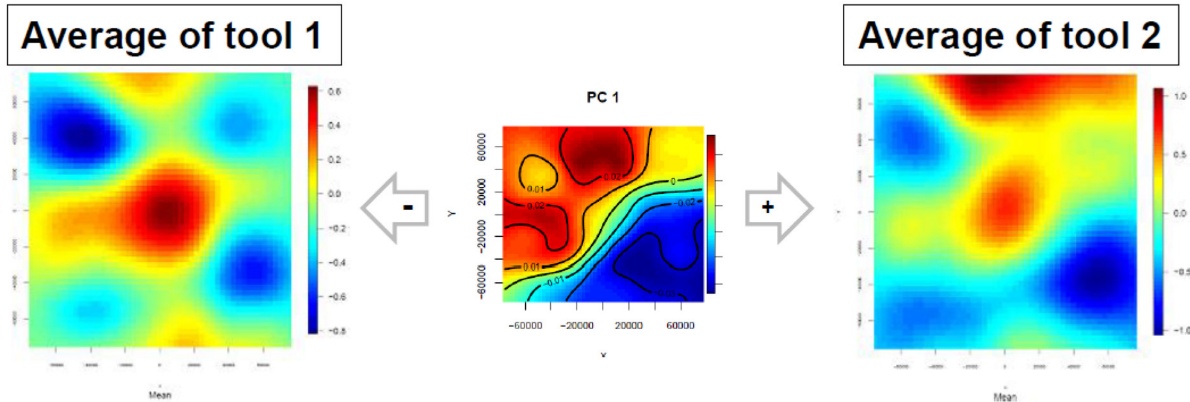

Figure 2. The two tools induce a subtle yet significant difference in the CD signatures. The average signature performance of tool 1 is depicted in the left panel. The average CD signature performance of tool 2 – shown in the right panel – is similar but more pronounced. Main differences are found at the upper boundary and in the lower right corner. The variation mode as identified in a PCA illustrates this observation (middle panel). Two compensation approaches are tested: a map based on a balanced sample of both tools thus either enabling production flexibility or a tool separation based approach.

Table 1. Typical parameters which have a substantial impact on global CD signatures and variation patterns. A principal component analysis identifies the patterns, which are classified by clustering. The relation towards the process parameters is identified by standard correlation analysis techniques. The tool parameter entry is marked bold face to highlight the use case for tool mismatches.

Parameter	Type	Learning step	Learning type
Tool 1, Tool 2	Global	A	Unsupervised
Resist status	Global	A	Unsupervised
Process step A,B,C	Global	A	Unsupervised
Mask geometry	Global	A	Unsupervised
Average pattern load	Global	A	Unsupervised

applications are ubiquitous in the context of smart phones it escapes the users due to the presence that these are very cleverly designed systems. Thus the power of the current machine learning algorithms cannot necessarily easily be exemplified by these applications.

However, there are popular landmarks where machine learning algorithms have recently proven their prowess in mastering domains of human intelligence. The first hallmark of this type is most likely the victory of the chess computer “Deep Blue”[2] against the then reigning world chess champion Gary Kasparov. Chess with its 8x8 fields and 32 counters is a game of simple rules with an immense complexity. This complexity results out of the vast amount of legal chess positions (around 10^{40}) which result of the movement patterns of the counters. The game is a game of perfect information, which means that each player is informed of all the events that have previously occurred, including the “initialization event” of the game. In the case of Chess, the optimal game strategy could in principle be computed by both players at any stage of the match. However, such a computational task is beyond the abilities of humans and task is in certain situations replaced by the perception and analysis of patterns and power lines. The vast number of possible chess positions is the reason why Claude Shannon proposed in the year 1950 that in setting up a computer for Chess the simple forward computation of all possible moves should be supplemented by a selection process[3]. In the case of Deep Blue the massive computational power was supplemented by a large Grandmaster game database. This combination constituted the base for selection of valid moves for “Deep Blue”.

This victory, however, was at that time only partially considered

Table 2. Typical parameters exerting a CD influence on the global and the local level. These parameters are used as covariates in the supervised learning step for setting up a CD compensation model. The tool parameter line is marked grey as a common compensation approach for both tools is tested.

Parameter	Type	Learning step	Learning type
Tool 1, Tool 2	Global		Supervised
Resist status	Global	B	Supervised
Process step A,B,C	Global	B	Supervised
Mask geometry	Global	B	Supervised
Average pattern load	Global	B	Supervised
Local pattern load	Local	B	Supervised
Position X,Y	Local	B	Supervised
Feature	Local	B	Supervised
Location relative boun	Local	B	Supervised

as a machine learning success, as no learning mechanism was implemented in the set up. Thus the ancient game of Go with the substantially more legal positions of $2.08*10^{170}$ was considered as a real litmus test for machine learning. In 2015 the general believe was that it would take another 5-10 years for having a computer with enough power to win against a reigning Go champion. This estimate was based on the assumption that the software would be set up in a manner similar to “Deep Blue”. As it turned out the 9th Dan holding Go player Lee Sedol lost to the Go machine “AlphaGo” in 2016. The key points in the “AlphaGo” set up are a Monte Carlo tree search guided by a value & policy network implemented using a deep neural network technology as well as constant learning cycles of the software[4].

These two major successes of machine learning in the field of games of perfect information were closely followed by a third milestone for machine learning concepts when the poker machine “Libratus” won against four poker professionals a 20 day tournament with 120,000 played hands. The set up of the machine learning algorithm for “Libratus” relies on a combination of counter factual regret minimization and a regret matching algorithm[5]. This set up proves to be highly adaptable to games of imperfect information such as poker. Games of imperfect information are characterized by the fact that each player is not perfectly informed of all the events that have occurred in the course of the game. In this implementation the learning phase of “Libratus” was performed

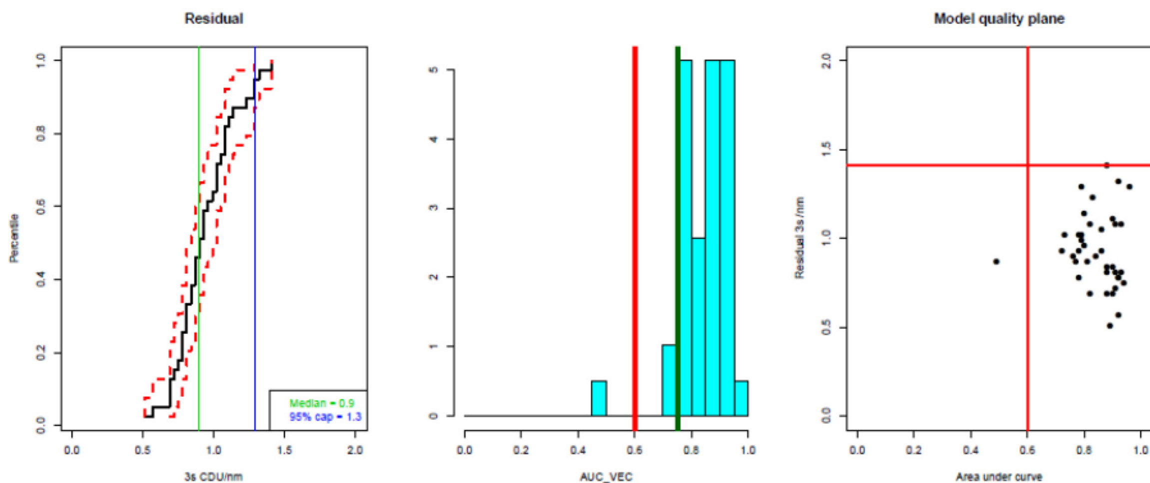

Figure 3. Model performance of the balanced model obtained by blending the auxiliary information into a balanced sample for model training. Model validation shows a good performance in the compensation residual (left panel) and the area under curve (AUC in the middle panel). The model quality plane shows a scatter plot of both values. Good model performance is given when the data lies in the lower right quadrant.

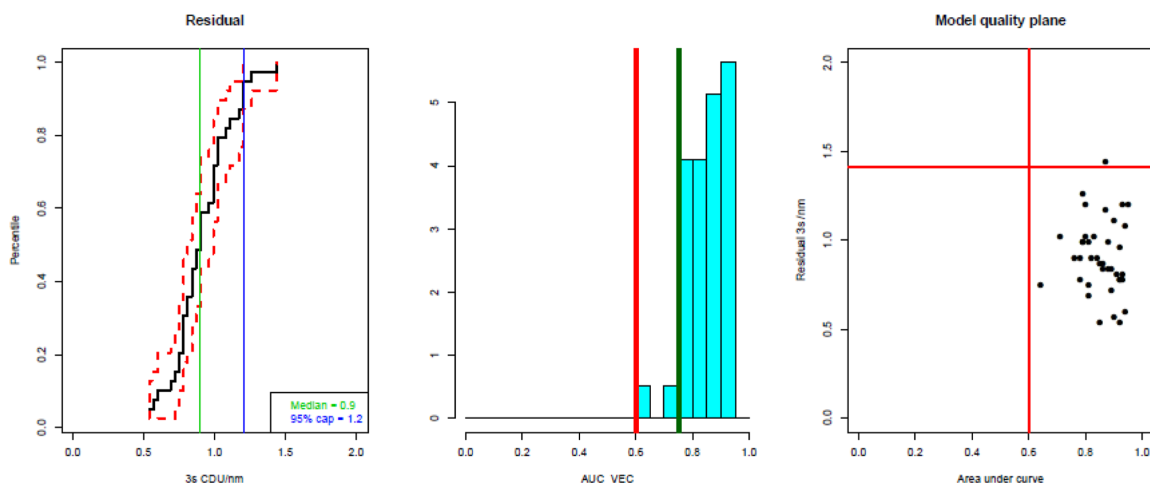

Figure 4. Model performance of the model with tool dedicated compensation maps. The performance for the compensation residual is only 0.1nm better than for the model obtained by the balanced sample (consider the 95% capability in the left panel). Also the area under curve performance is only marginally better than for the model based on the balanced sampling (middle panel).

in the nights between the match days. Significant improvement of the software during the tournament was noted and reported by the opponents. These results immediately prompt the question as to the relation of machine learning to the vast field of artificial intelligence which is depicted in figure 1. Machine learning is fast growing subfield of artificial intelligence, largely contributing to the overall growth of the field.

The brief journey along the major milestones of machine learning in the context of classic games shows on the one side the enormous potential of modern machine learning set ups and on the other side that the machine learning set up needs to be tailored to the needs of the learning task. This paper discusses how the concepts of machine learning were used in the context of mask manufacturing in order to control the uniformity of the critical dimensions (CDU control). The set up is detailed together with its motivation and how the set up enables the use for dealing with production problems such as modest tool mismatches as well as the efficient modeling of short range boundary effects.

2. Architecture of the CD Map Control Model

2.1 The parameter space

Meeting the demands on critical dimensions (CD) in mask manufacturing is of critical importance for the lithographical performance of each mask in the waver production process. Thus the control of the CD uniformity (CDU) is one of the key objectives for the mask manufacturing process. The contributions to the CDU of a mask can in general be decomposed into a systematic and a noise contribution[6,7]. The process control mechanism discussed in this paper acts on the long range systematic contributions of the CD uniformity. The basic set up of the machine learning concept relies on a sequential combination of a principal component analysis[8] followed by a recursive partitioning of the data[9,10]. The resulting decision tree is utilized for a spatially resolved prediction of the CD deviations at positions x and y over the mask[11]. This systematic CD deviation is than utilized as input for the electron beam (EBM) writer. The EBM writer thus modulates electron dose and proximity effect corrections accordingly for optimal CDU results. In general

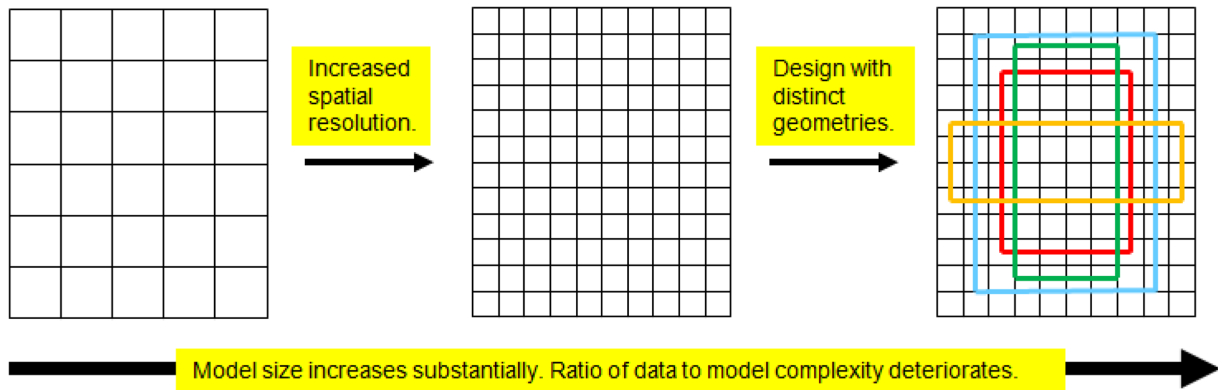

Figure 5. Increasing the spatial resolution of the machine learning algorithm increases the model complexity: an increase of the resolution by the factor 2 increases the number of bins by 4. This in turn increases the number of partitions for the machine learning. The boundaries of distinct layout geometries are exhibited by the colored lines in the figure on the right. A placement independent boundary effect induces a CD shift; this leads to a pronounced variability which can be challenging for machine learning based on a limited amount of data.

the frame work within which a machine learning set up operates in mask manufacturing is given by:

a) A high variability of the learning data in the presence of a small product number,
b) A need for quick model updates based on limited amounts of training data,
c) The ability to mitigate modest process mismatches between tools and processes.

Any machine learning set up for CDU control needs to fulfill these requirements to a certain extent. The remainder of this paper will describe in detail how the particular set up serves to fulfill these requirements.

The CD(x,y) distribution across a mask is the results of a complex non-linear interaction of global influence parameters such as tool geometries, average mask clear-field and mask geometry with local influence parameters such as loading transitions, feature variations and boundary effects. This leads to the following formulation:

$$CD^{i}(x,y) = f\,[g(x,y,p^{i}_{1}),x,y,p^{i}_{2}] + \nu_{xy} \quad (1)$$

where "i" is a mask index, and p_1 and p_2 are the corresponding parameter vectors of global and local influence parameters. The noise contribution is denoted by ν_{xy}. A common approximation of this function is obtained by assuming that the overall CD(x,y) distribution can be described by a linear superposition of a function describing the influence of global effects g_G and local effects f_L:

$$CD^{i}(x,y) = f_L(x,y,p^{i}_{2}) + g_G(x,y,p^{i}_{1}) + \nu_{xy} \quad (2)$$

The equation (2) is simplified when considering a large mask ensemble where due to the pronounced design variations the local contributions f_L are averaged out. Thus for the purposes of learning the typical global patterns of a mask process we can use the following approximation:

$$\langle CD^{i}(x,y)\rangle = \langle f_L(x,y,p^{i}_{2})\rangle + \langle g_G(x,y,p^{i}_{1})\rangle + \langle\nu_{xy}\rangle \quad (3)$$

$$\sim \langle g_G(x,y,p^{i}_{1})\rangle \quad (4)$$

The first step of our learning task is to learn the typical global CD signatures $\langle g_G \rangle$, so that i) outlier can be identified, ii) typical signatures can be classified and iii) the variation patterns are obtained. To this end we use the unsupervised learning method of a principal component analysis to enable the extraction of points i) through iii). This principal components analysis (PCA) reduces the dimensionality of the problem substantially thus leading to a representation of each signature by the PCA scores of the associated modes of variation[12,13]. This means that outliers as well as typical signatures can by identified by standard techniques. The relationship to global process parameters as mentioned in table 1) is also easily accessible by standard correlation analysis. In this learning step the observed typical signature patterns are tested for association with the parameter values: is a certain tool combination responsible for a special CD signature, or is the resist age related to the expression of a certain CD signature. This type of analysis reaches beyond the unsupervised learning step, as the target quantity of CD is related to the coefficients of the PCA. The specific analysis steps are a hierarchical clustering step where outliers are identified using a cut off value of 95% of the overall height. Following this, we identify typical signatures using a "kmeans" clustering. The association with the global parameters is done using a partitioning analysis. This results in a characterization of each mask data set with auxiliary data reflecting its outlier characterization, signature type and tool/process relation.

Based on this data set we can extract a balanced sample[14] which is used as a training set for the second learning step. The balanced sample ensures that the training set has the same statistical properties as the full data set. This is one of the important steps in the mask manufacturing machine learning set up as it allows blending the signature and process information into a representative learning sample. Two major goals are achieved: the shortcoming of portioning tree algorithms which are very sensitive to the training data are overcome as the sample is a good representation of the full production data set and modest process mismatches are represented in the training set as the distinct characteristics induced by mismatches are represented. This property is particularly important in cases where for capacity reason two distinct tools are used within production which cannot be compensated for separately. In our specific case any tool which is not an electron beam writer is of this type, as only the EBM writers exert the CD compensation and mask routing after writing needs to be flexible to ensure maximum throughput. In table 2) for example the parameter "Tool 1, Tool 2" is marked grey, as we like to treat both tools equally in the compensation approach (learning step "B") , even though a distinct behavior of both tools has been noted in the learning step "A".

The balanced sample identified in learning step "A" enters the learning step "B" as a training set. In this step a partitioning tree

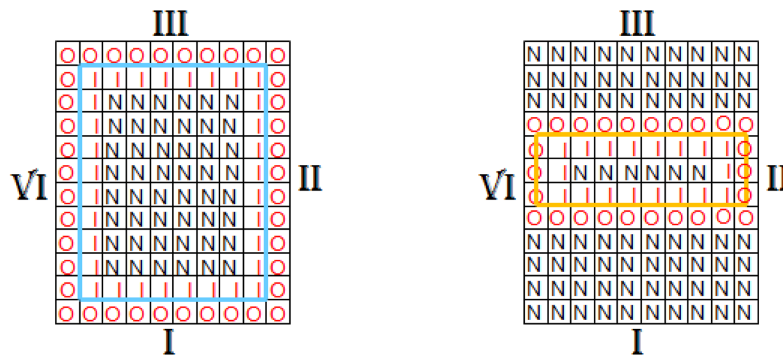

Figure 6. The introduction of four new covariates "I", "II", "III" and "IV" with three possible values "I", "O" and "N" reduces the problem complexity. The roman numerals mark the four sides of each masks; "I" stands for inner, "O" for outer and "N" for none. A box marked with "N" is not in the immediate vicinity of the active boundary. A box marked with "O" in the column "III" is on the outside of the upper boundary of the active area.

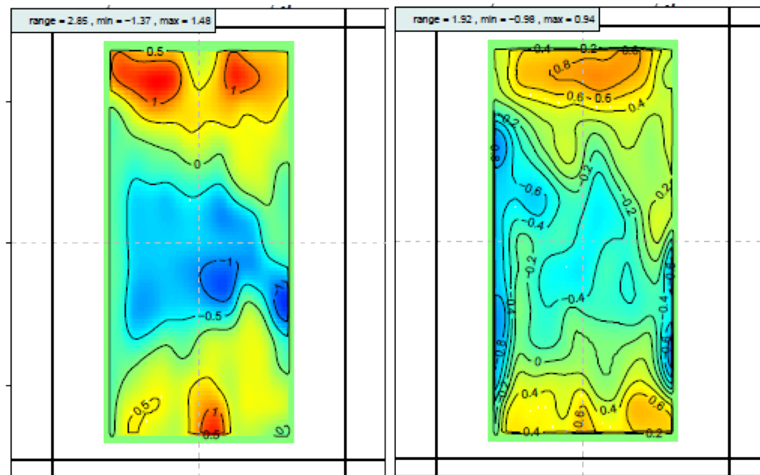

Figure 7. Comparison of two compensation maps obtained for the same mask with two distinct models. The map in the left panel is obtained with coarse resolution and no dedicated boundary treatment. The map in the right panel is obtained with the fine resolution and a dedicated boundary treatment. This map shows a substantially improved performance at the boundary. In this case the compensation residual is reduced by 25% and is increased by 12.5%.

approach is used to explain the CD distribution using a full set of covariates (table 2)) describing the influence of local as well as global parameters on the CD signature. Thus the aim is to learn the full signature CD(x,y) ~ $f_L + g_G$ on each mask. Following the learning phase the model is validated in the full data set using two parameters for asserting the map quality. The first parameter is the compensational residual which measures the remaining signature after the correction map has been applied. This value is largely determined by run to run variations as well as by suboptimal CD compensation. The second value is the area under curve (AUC)[15] which measures the shape congruence of the CD compensation map with the measured CD signature.

For the example discussed in this paper a subtle tool mismatch as depicted in figure 2 is considered in the machine learning based compensation approach.

Disregarding the subtle yet detectable difference in tool induced CD signature performance as depicted in figure 2 results in out of specification conditions for masks. This means that the aspect of even modest tool mismatches is significant for CD control in the mask manufacturing. For production flexibility an approach where both tools can be used with identical compensation maps is largely preferable to an approach with separate compensation maps. Thus two compensation machine learning set ups were tested. The first approach blends the tool information by utilizing a balanced sample which explicitly takes the tool as a balancing parameter into account but computes an identical map for both tools. The second approach computes distinct maps for each tool. The data presented in figures 3) and 4) allows a detailed performance comparison of the two machine learning settings. The left panel of each figure shows the capability curve for the compensation residual. The difference between the two settings is marginal with the set up using tool specific maps outperforming the balanced sample only by 0.1 nm. A similar finding is documented for the area under curve for which the performance histogram is given in the middle panel of figure 3) and 4). Thus it can be concluded that the splendid blending of the auxiliary information in the balanced sample of the training set leads to a model performance where the impact of the distinct tool performance can be averaged as to yield the same capability as the dedicated set up. The balanced sample approach to CD control is with respect to the production requirements of flexibility and maximum capacity far more preferable than tool specific control settings. It should be pointed out that the particular set up of performing two sequential learning steps which are linked by the balanced sample selection enables this kind of machine learning approach. Thus in this section it was demonstrated that this set up has the ability to mitigate modest

mismatches between tools and their corresponding processes in order to achieve a suitable process capability. The next section will focus on the importance of identifying good covariate – i.e. explanatory variables – for a successful application of machine learning strategies.

2.2 Model set up: boundary effects

The basic set up of the machine learning algorithm employs a spatial discretization of the mask field. An array of the N x N equally sized boxes is thus the basis of CD compensation. This specific machine learning set up has the flexibility to accommodate a variety of physical effects observed in the manufacturing process. The CD step at the geometrical boundary of active area is such a significant effect. It is observed, that the transition induces a typical CD shift of 1nm to 2nm. This effect needs to be actively compensated by the CD map in order to achieve a good CD capability.

As the CD dynamics at the boundary are induced on a very short spatial range, an increase of the spatial resolution of the machine learning model by 50% is required. However, such an increase in spatial resolution more than doubles the overall model complexity (see figure 5). In order to limit the complexity increase 4 additional covariates are introduced to the model. Each covariate has the four possible values "I", "O" and "N". The values mark the four possible boundaries associations of each box (see Figure 6). The values denote the boundary relation: "N" indicates no vicinity to the boundary where "I" and "O" denote a location at the inner/outer boundary. This set up enables the determination of the boundary effect independent of the spatial location. This in turn simplifies the learning task for the machine learning algorithm thus improving the model performance while reducing model complexity.

The learning task in the presence of a pronounced boundary effect is relatively complex. The short ranged nature of the boundary effect implies that the spatial resolution of the model binning needs to be increased as to reflect mainly the affected region (panel from left to right in figure 5)). This increases the computational effort substantially. Another dimension of complexity is added by the fact that the boundary varies considerably with the mask design as indicated by colored lines in the right most panel of figure 5). The increase in spatial resolution is in this case the major factor in improving the compensation performance. An overall compensation improvement of 25% is achieved. The difference in the compensation map between the low resolution approach (left panel) and the high resolution approach with dedicated boundary variables (right panel) is depicted in figure 7). The map in the left panel lacks the boundary dynamics required for an optimal compensation. The introduction of the dedicated boundary parameter reduces the update time from 78h to 34h which is a saving of nearly two days. As mentioned in the introduction, the constant update procedure is a major strength of machine learning approaches. This means that a shortening of the update cycle by 44h is a key achievement in the use of machine learning for CD control. Thus the introduction of optimal covariates in machine learning problems is of major importance for ensuring good predictive capabilities as well as reducing the computational load to manageable sizes.

3. Conclusions

This paper gives a detailed account of using machine learning in the context of mask manufacturing. Machine learning is a rapidly growing field at the interface of statistics and computer sciences. The applications of machine learning in the context of many internet related functionalities are already quite common and successful. Its use in manufacturing context, however, is only starting. We find - in the context of mask manufacturing - that the ability to systematically turn data into actionable insights opens the avenue for improving compensation methods substantially.

4. Acknowledgements

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Industry Briefs

Gartner Says Worldwide Semiconductor Revenue to Reach $400 Billion in 2017

Worldwide semiconductor revenue is forecast to total $401.4 billion in 2017, an increase of 16.8 percent from 2016, according to Gartner, Inc. This will be the first time semiconductor revenue has surpassed $400 billion. The market reached the $300 billion milestone seven years ago, in 2010, and surpassed $200 billion in 2000.

“A shortage of memory is creating a boom in the overall semiconductor market,” said Andrew Norwood, research vice president at Gartner. “Memory vendors have been able to increase their price for DRAM and NAND, driving revenue and margins higher.”

The booming memory market, with revenue forecast to increase 52 percent in 2017, is expected to shake up semiconductor market share rankings. “As the largest memory supplier, Samsung Electronics is set to gain the most,” said Mr. Norwood. “This gives Samsung its best shot at capturing the No. 1 position from Intel for the first time.”

Intel dethroned NEC for the No. 1 position in semiconductor rankings in 1992 and has held it ever since. Samsung captured the No. 2 position in 2002 and has held that since.

“What the memory market gives, the memory market takes away,” said Mr. Norwood. “The memory bubble is expected to go bust in 2019 as memory vendors add new supply and Samsung could lose a lot of the gains it makes this year and next.”

Canon provides nanoimprint lithography manufacturing equipment to Toshiba Memory’s Yokkaichi Operations plant

TOKYO, July 20, 2017—Canon Inc. announced today that the company has provided the FPA-1200NZ2C, semiconductor lithography equipment that utilizes nanoimprint lithography (NIL) technology which Canon has been continuously developing since 2004, to leading provider of semiconductor memory solutions Toshiba Memory Corporation’s Yokkaichi Operations plant. The provision of this equipment represents significant progress toward semiconductor device mass production that employs nanoimprint technology.

Facing the difficult challenge of circuit scaling, or miniaturization—the key to the advancement of semiconductor devices—Canon has been carrying out R&D since 2004 in the field of next-generation semiconductor manufacturing equipment that utilizes NIL technology which achieves even more detailed circuit patterns as small as 10 nm at an even lower cost, compared with photolithography. As part of this effort, Canon welcomed American company Molecular Imprints, Inc. (now Canon Nanotechnologies, Inc.) into the Canon Group in 2014.

Nanoimprint lithography manufacturing equipment utilizes a patterning technology that involves the field-by-field deposition and exposure of a low viscosity resist deposited by jetting technology onto the substrate, faithfully reproducing patterns with a higher resolution and greater uniformity compared to those produced by photolithography equipment. This technology simplifies the cutting-edge lithography processes used to manufacture semiconductor devices, to make possible a significantly reduced CoO (Cost of Ownership).

Canon’s delivery of the FPA-1200NZ2C NIL manufacturing equipment for semiconductor mass production to the Yokkaichi Operations plant of Toshiba Memory further accelerates progress toward the world’s first semiconductor memory mass production to utilize NIL technology.

TSMC Logs First 10nm Sales

TAIPEI — Taiwan Semiconductor Manufacturing Co. (TSMC) has recognized its first revenue from 10nm products, trailing Samsung, its main rival in the foundry business, by nearly four months.

TSMC said that 10 nm accounted for 1 percent of its overall revenue during the second quarter of this year. In March, Samsung announced its first 10-nm products, including the company’s Exynos 8895 SoC as well as Qualcomm’s Snapdragon 835.

TSMC expects to exit a slump that saw its second-quarter sales in dollar terms edge up just 3.2 percent from the same period a year ago. The company, which makes mobile communications products for Apple and MediaTek, said that an inventory correction among fabless customers will probably end during third quarter this year.

TSMC also said its 7-nm yield is ahead of schedule and it expects a fast ramp in 2018. The company plans to insert several extreme ultraviolet (EUV) layers at 7 nm, but declined to provide details. The company also plans to offer a 7-nm plus node that it expects will allow customers easy migration from 7 nm.

At this point, TSMC has about 30 tape outs for 7-nm products.

TSMC added that its 5 nm roadmap is on track for a launch in the first quarter of 2019.

Join the premier professional organization for mask makers and mask users!

About the BACUS Group

Founded in 1980 by a group of chrome blank users wanting a single voice to interact with suppliers, BACUS has grown to become the largest and most widely known forum for the exchange of technical information of interest to photomask and reticle makers. BACUS joined SPIE in January of 1991 to expand the exchange of information with mask makers around the world.

The group sponsors an informative monthly meeting and newsletter, BACUS News. The BACUS annual Photomask Technology Symposium covers photomask technology, photomask processes, lithography, materials and resists, phase shift masks, inspection and repair, metrology, and quality and manufacturing management.

Individual Membership Benefits include:

- Subscription to BACUS News (monthly)
- Eligibility to hold office on BACUS Steering Committee

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Corporate Membership Benefits include:

- 3-10 Voting Members in the SPIE General Membership, depending on tier level
- Subscription to BACUS News (monthly)
- One online SPIE Journal Subscription
- Listed as a Corporate Member in the BACUS Monthly Newsletter

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Calendar

2017

SPIE Photomask Technology and SPIE International Conference on Extreme Ultraviolet Lithography 2017
11-14 September 2017
Monterey, California, USA
www.spie.org/puv

2018

SPIE Advanced Lithography
25 February-1 March 2018
San Jose Marriott and
San Jose Convention Center
San Jose, California, USA
www.spie.org/al

Photomask Japan 2018
18-20 April 2018
Pacific Yokohama
Yokohama, Japan

The 34 European Mask and Lithography Conference, EMLC 2018
19-20 June 2018
MINATEC Conference Centre
Grenoble, France

SPIE is the international society for optics and photonics, an educational not-for-profit organization founded in 1955 to advance light-based science and technology. The Society serves nearly 264,000 constituents from approximately 166 countries, offering conferences and their published proceedings, continuing education, books, journals, and the SPIE Digital Library in support of interdisciplinary information exchange, professional networking, and patent precedent. SPIE provided $4 million in support of education and outreach programs in 2016. www.spie.org

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You are invited to submit events of interest for this calendar. Please send to lindad@spie.org; alternatively, email or fax to SPIE.