Special Section Guest Editorial: Deep Learning

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Deep learning (DL) is one of the most exciting fields in artificial intelligence right now. It's still early days for this technology, but many believe that DL will totally change the lithography and photomask industries with better modeling and faster computations for automating the optimization of equipment and processes. This special section of JM3 highlights some exciting DL applications in the lithography and photomask industries.

The eight papers included in this special section cover all the aspects of DL that I sought in the call for papers. There are both algorithm and application papers advancing the state of the art in modeling, simulations, optical process correction (OPC) and inverse lithography technology (ILT), mask manufacturing, metrology, and inspection.

1 Description of DL Technologies and Algorithms

We have one paper seeking to advance the DL algorithms itself. A paper by Akpabio and Savari and tries to answer a fundamental question in DL: how to judge the reliability of the predictive performance of machine-learning models. To many people, DL is a black box, so building a correlation between the model and its predictability is very useful for DL applications.

2 Digital Twin Technology and its Applications

Yan et al. developed a wafer scanning electron microscope (SEM) digital twin using U-Net. SEM-image-related DL applications are one of the most promising areas to apply DL in semiconductor manufacturing. Rigorous SEM image simulation is too slow, and extracting contour and CD from noisy SEM images is really challenging for conventional algorithms. The paper shows the great potential to have a fast and accurate SEM image digital twin for even full-chip applications, such as die-to-database e-beam inspection.

3 Use of DL to Create More Accurate Models (Mask 3D Models, Resist Models, Neutron Transmutation Doping Models, etc.)

Extreme ultra-violet (EUV) mask 3D (M3D) modeling is a natural application for DL. There are two papers in this area, but with different approaches. Tanabe, Sato, and Takahashi considered mask near field amplitude as a modification from amplitude of the thin mask model. They used the difference of such amplitude to train a convolutional neural network (CNN). This is similar to the conventional approach that sought to simulate M3D using extra special kernels by replacing such special kernels with deep neural network kernels.

Yuan et al. presented a very different approach for the same problem: they used a generative adversarial network (GAN) to learn the paired mapping between the distribution of the mask near field. Then this EUV absorber scattering model was combined with the reflector model afterward to form the complete EUV mask model.

4 Applying Deep Learning in OPC and ILT

Applying deep learning to OPC and ILT is another hot area. The paper by Ciou et al. is a good example in this area. They applied a GAN to train the neural network to generate what they called an ILT image, basically a continuous tone mask, where the sub-resolution assist features were extracted.

5 DL in Geometry Grouping and Defect Classification

Gai et al. contributed a paper on hotspot grouping based on geometries using DL. They identified that the bottleneck of DL-based hotspot detection has too many clips from a full chip design. Therefore, they tried to group similar geometries using a CNN in order to reduce the number of clips run for hotspot classifications.

Defect detection and classification are natural applications of DL. Ahn et al. proposed a DL approach using an object-recognition neural network for the classification and detection of defects in SEM images featuring line-space patterns. Evanschitzky et al. explored SEM image defect detection and classification for the Zeiss eBeam EUV mask repair tool. They presented a hybrid and modular approach based on a combination of several DL networks and analytical methods.

6 DL Training Data Generation with Simulations and Digital Twins

Evanschitzky et al. also demonstrated a good practice in DL in semiconductor manufacturing – using rigorous simulation to generate the training data.

As we all know, DL is "programmed" by data. All the papers point out how important it is to have the right kind of data and the right volume of data. Some papers point out specific techniques used for data augmentation, a DL terminology for morphing existing data to increase the amount of training data available.

There's another way to add data, and specifically to add data of any arbitrary type: digital twins. Yan et al. describe a digital twin, which is a critical tool for being able to generate new training data as confusion in the network is identified. Ciou et al. use the "slow" ILT to generate training data. The EUV M3D modeling by Yuan et al. has rigorous simulators to generate training data. Investing in digital twins is emerging as a critical success factor for any DL project.

7 DL Tricks and Best Practice

Many authors shared the tricks and best practice they learned. To name a few: Ahn et al. showed an optimized network and data augmentation strategies (flipping and mixing images from simulations) to achieve a significant increase in the performance of the network. Gai et al. used 2D Fourier transforms to eliminate the influence of mirror transformation and patterns offset. Yan et al. demonstrated graphics processing unit computing is good for inference as well as training – they accelerated their SEM image generation by 80 times compared to central processing unit computing.

In summary, this Special Section on Deep Learning will give you a comprehensive overview of major active areas of DL in the lithography and photomask fields.

The section would not have been possible without the contributions from the authors, so I'd like to thank them all. I would also like to thank our reviewers: Every paper has been reviewed by two or more reviewers multiple times. Their expertise in DL and their detailed feedback helped the authors to correct any mistakes, and to improve their content significantly during the process. I would like to thank Ajay K. Baranwal, the director at the Center for Deep Learning in Electronics Manufacturing (CDLe). He provided me with lots of DL expert opinions and in-depth feedback to those papers. A special thanks goes to Dr. Harry Levinson, the editor-in-chief of JM3 – without his encouragement and advice I wouldn't have been able to get this special edition done! Last, I appreciate the editing and publishing team of SPIE and JM3 – without them you wouldn't be able to see all of these beautiful papers.