Process and material design for advanced VLSI process assisted by deep learning

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Application of artificial intelligence to semiconductor processes is becoming indispensable for process and material optimization in mass production. For example, in the field of lithography, it is used to detect hot spots on layouts. These are usually learned from the big data such as huge amounts of experimental results and experience, and are used to design processes. However, deep learning could not well work when there is little teaching data, such as when dealing with unknown materials, during the process or material development stage, and it becomes difficult to predict the results and optimize the process.

In this talk, we introduce our approach using classical back propagation neural network, (BPNN) to support the development of new materials and processes by using a small amount of teaching experimental data during the process and material development stage and supplementing it with simulation results or data augmentation.

Case 1. CMP process design for plastic material for RDL in Chiplet [1]

For the RDL (Redistribution Layer) process, CMP (Chemical Mechanical Polishing) of organic insulating materials is demanded, but no data exist for CMP processing. Then a large number of experiments are required to design the polishing conditions. Therefore, the dependency of the polishing rate on the process conditions was predicted using deep learning from a small number of teaching experiments in which the process conditions were alternated.

For the data augmentation, the training data were randomly augmented using a Gaussian distribution with a standard deviation σ of the experimental error for the equipment used. As a results, the polishing rate is successfully predicted within an error range of about 10%, which is very useful for setting the rough process conditions when simultaneously polishing with wiring metal.

Case 2. Resist synesis optimization [2]

In resist synthesis, the ratio of components is an essential factor that determines performance, but extensive experimental verification is required. Here, the exposure-development characteristics were measured for trial resists with several different synthesis ratios, and these were used as training data to predict the exposure-development characteristics for other synthesis ratios. From these characteristics, the gamma value and sensitivity were extracted, and the synthesis ratio with the best gamma value and sensitivity was predicted. When the resist was actually synthesized with that synthesis ratio, the gamma value and sensitivity were optimized as predicted. This made it possible to eliminate the need for dozens of optimization experiments.

Case 3. Nanoimprint process design using a hybrid learning system with numerical simulation [3]

In the nanoimprinting, functional materials could directory processed; however, the process conditions are not known for new materials and process. For unknown materials, a small number of experiments were performed with different material compositions, and the optimal value of the composition was predicted by deep learning using data augmentation. That is, the simulation results when the pressing conditions (relative pressing pressure and structure (relative shape)) are changed are learned and a teaching data is created. After checking which relative pressing pressure the experimental results apply to, deep learning is used to predict the molding results for changes in real dimensional pressure and shape. Here, for PVA (Polyvinyl Alcohol) with different Glycerin contents, the Glycerin content was optimized, and it was confirmed that the corresponding process results predicted results were in good agreement with the verification experiment.

As demonstrated above, for unexplored materials and processes, it has been shown that it is possible to effectively predict results using deep learning by inflating fewer experimental results and linking them with numerical simulations. This shows that artificial intelligence can be useful in supporting the optimization design of new materials and processes for some cutting-edge processes.

References

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[3] Y. Hirai, et al., *Nanomaterials* **12**, (2022) 2571