Delft University of Technology
ASML

Project: Neural networks-based surrogate for solving non-linear wafer deformation

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Topic

In lithography, wafer heating induces unwanted deformations that must be compensated in a feedforward manner. Accurately resolving non-linear and history-dependent effects typically requires time-consuming iterative solvers, making real-time computation challenging; see Figure 1. Recent advances demonstrate that physics-informed neural networks (PINNs) [3, 4] can serve as efficient surrogate models, trained without the need for extensive simulation data. However, applying these networks at full wafer scale while capturing local, high-frequency effects with sufficient accuracy remains a significant challenge.

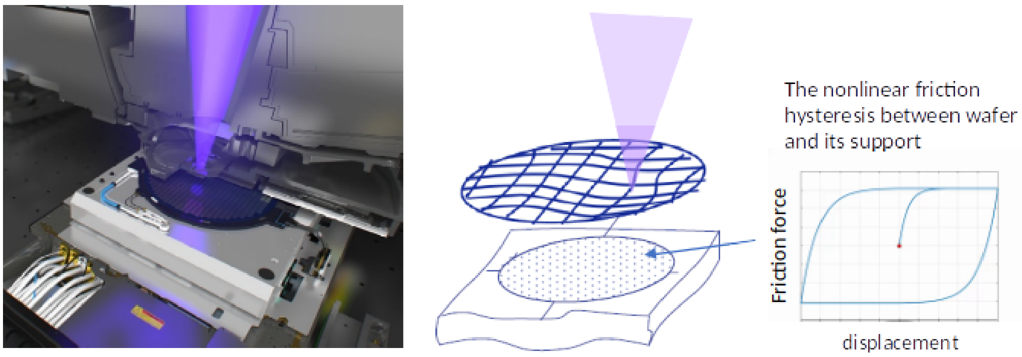

Figure 1: Light induced deformation and slip of the wafer

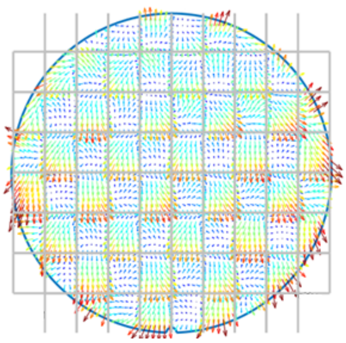

Figure 2: Example wafer deformation with fields shown with a grid

Wafers are exposed in repeating, partially rectangular regions called fields, as shown in Figure 2. Domain decomposition-based neural network methods are especially promising for capturing such localized effects. In the context of neural networks, domain decomposition can be implemented using classical iterative techniques [1] or by embedding decomposition principles directly into the neural network architecture [2]. The aim of this master thesis and internship project is to develop a neural network model and training strategy based on domain decomposition principles that can accurately predict time-dependent, non-linear wafer deformation. The ultimate goal is to create a surrogate model that is general, accurate, and fast enough for real-time use.

For this position, it is expected that the candidate onboards at ASML and is present at least 2 days/week in Eindhoven/Veldhoven offices. An intern allowance is also offered per ASML intern policy.

Contact

Are you interested or do you have any questions? Send an email to Alexander Heinlein (a.heinlein@tudelft.nl) and/or Ozan Celik (ozan.celik@asml.com).

References

[1] V. Dolean, S. Gratton, A. Heinlein, and V. Mercier. Two-level deep domain decomposition method, Aug. 2024. arXiv:2408.12198.

[2] V. Dolean, A. Heinlein, S. Mishra, and B. Moseley. Multilevel domain decomposition-based architectures for physics-informed neural networks. *Computer Methods in Applied Mechanics and Engineering*, 429:117116, Sept. 2024. ISSN 0045-7825. doi: 10.1016/j.cma.2024.117116.

[3] I. Lagaris, A. Likas, and D. Fotiadis. Artificial neural networks for solving ordinary and partial differential equations. *IEEE Transactions on Neural Networks*, 9(5):987–1000, Sept. 1998. ISSN 1941-0093. doi: 10.1109/72.712178. Conference Name: IEEE Transactions on Neural Networks.

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