Model Predictive Control for Large-scale Thermo-mechanical Systems

MSc project at ASML Research Mechatronics & Control
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Background

At ASML Research, advanced modeling, identification, and control techniques are studied in order to comply with desired overlay performance for the next generation lithography machines. These machines are critical in the production of Integrated Circuits (IC's). In the next generation Extreme Ultra Violet (EUV) machines, imaging distortions due to the inevitable presence of thermal disturbances induced by the exposure become more critical in the overall imaging performance as the source power demand is increasing rapidly, see also Figure 1.

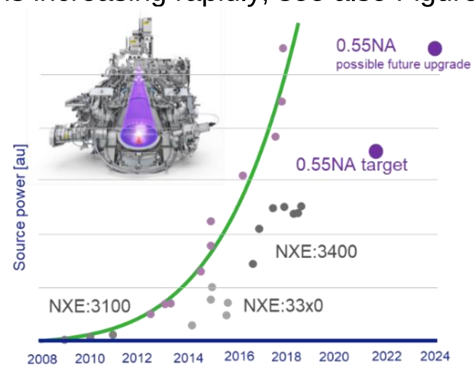

Figure 1: Evolution of the source power over time[1]

The increasing demand for higher source powers is due to the following two reasons:

1. The throughput demand of future lithography machines requires higher source powers,
2. A higher source power allows a higher exposing dose which results in improved local critical dimension uniformity (CDU) and thus better yield.

To overcome the image distortions due to the increasing thermal disturbances, there is a strong need for methodologies to actively suppress the deformations induced by these thermal loads.

Figure 2: NXE:3400B system

[1] Source: Jan van Schoot, Eelco van Setten, Kars Troost, Frank Bornebroek, Rob van Ballegoij, Sjoerd Lok, Judon Stoeldraijer, Jo Finders, Paul Graeupner, Joerg Zimmermann, Peter Kuerz, Marco Pieters, Winfried Kaiser, "High-NA EUV lithography exposure tool progress," Proc. SPIE 10957, Extreme Ultraviolet (EUV) Lithography X, 1095707 (14 March 2019);

The main challenges in suppressing the thermal loads include dealing with the limited ranges of thermal actuators and with the large variety of spatially distributed thermal loads that can occur. For this purpose, the use of model predictive control (MPC) schemes is being investigated as it allows to explicitly take into account the presence of input and performance constraints. In Figure 3, a typical MPC scheme is illustrated. The main idea of MPC is as follows:

- Given a state-estimate, a dynamical model, a cost function and input/output constraints, an optimal control input sequence is computed over a finite horizon. This optimization problem is also referred to as the finite horizon optimization problem.
- Only the first element of this sequence is implemented on the actual system.
- At the next time step, the optimization procedure is repeated using an updated state-estimate that is based on new sensor measurements.

Since the optimization procedure is repeated at every discrete time-step, the principle of feedback is present.

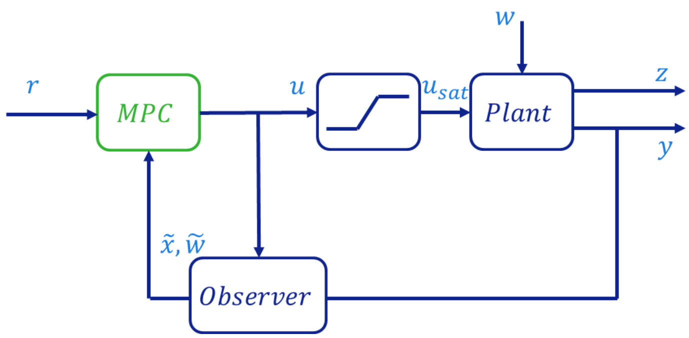

Figure 3: Schematic illustration of the MPC scheme where z denotes the performance signal, y the measured output, w ($\tilde{w}$) the (estimated) disturbance acting on the plant, $\tilde{x}$ the estimated state of the plant, and u (u_{sat}) the (saturated) control input of the plant.

To accommodate for the large variety of thermal loads, high fidelity (finite-element) models need to be considered in the MPC scheme. Within ASML, thermo-mechanical systems are typically modeled via the finite element method (FEM) resulting in a dynamical system with large state dimensions (>50.000). To be more specific, the thermal behavior of the model is given by

$$E\dot{T} = AT + B_u u + B_w w_{euv} \quad (1)$$

where T denotes the thermal state vector, u the actuation signal, w_{euv} the disturbance signal and E, A, B_u *and* B_w (sparse) system matrices. The deformations induced by the thermal loads can be computed by solving

$$K_T f(T) + K_M d = 0 \quad (2)$$

where K_M denotes the (sparse) mechanical stiffness matrix, K_T the (sparse) thermal stiffness matrix and f is a non-linear function that represents the temperature-strain characteristics of the material.

As the targeted sampling time for the controller is in the order of seconds, an important aspect in the design of an MPC scheme is the demand of computational resources of the on-line optimization scheme in terms of memory, scalability and overall computation time. In previous work, it is shown that the bottle-necks of solving the finite horizon optimization problem are

1. computing a particular response of the system over a finite horizon with the most recent state-estimate as initial condition.
2. computing the thermal-induced deformation.

Let us emphasize that the finite horizon optimization problem needs to be solved at each discrete time instant and thus includes the two computations mentioned above.

Assignment

The objective of the MSc project is to investigate efficient numerical methods (in terms of memory, scalability and overall computation time) that can be exploited in the context of model predictive control for both the thermal as the mechanical part of the system. To be more specific, in this project the following techniques might be explored:

Deflation (possibly based on model order reduction techniques)
Deflation is a well-known technique for removing the slowly converging components in iterative methods. A key ingredient in this technique is choosing a suitable deflation subspace. In particular for the thermal domain, using the orthogonal projections resulting from model order reduction techniques (such as Krylov subspace model order reduction methods or proper orthogonal decompositions) to construct the deflation subspace is a promising direction.

(Adaptive) algebraic multi-grid methods
Next to deflation, multi-grid methods is a common method to improve the converging properties of iterative methods. The high fidelity models used at ASML unstructured grids with a mixture of different element types. For this reason, it is of interest to investigate algebraic multi-grid methods that do not rely on the availability of geometric information. Classical algebraic multi-grid methods work effectively for so-called M-matrices but the converging behavior degrades significantly for matrices that do not have this property such as thermal capacity and stiffness matrices resulting from finite-element methods. To overcome this limitations, adaptive algebraic multi-grid methods have been proposed in which the smoother, prolongation and the coarsening process are adapted to the slow converging components in the iterative scheme. The latter procure might also benefit from model-order reduction techniques.

Space-time discretization:
As mentioned before, computing a particular response of the system over a finite horizon is one of the computational bottlenecks in solving the finite horizon optimization problem corresponding to the MPC scheme. Typically, this solution is computed in a sequential fashion over time using separate spatial and temporal discretization schemes. To speed up the computation, it is of interest to examine integrated spatial and temporal discretization schemes that allow to exploit parallel computing for both the spatial as the temporal domain.

Domain decomposition:
Due to the rapid developments in multi-processing technology, an important property in numerical methods is scalability. For this purpose, domain decomposition techniques in which the computation corresponding to the subdomains can be distributed over multiple processors are of interested.

The effectiveness of the proposed methods will be evaluated by means of a numerical case study with a numerical model that represents an optical element in an EUV machine with various numbers of states, actuators and sensors.

Deliverables

- Short literature study
- Presentations in control meetings @ASML
- Tooling (compatible with MATLAB)
- Final MSc report

Related references

General info about MPC:

Lecture notes Alberto Bemporad: http://cse.lab.imtlucca.it/~bemporad/mpc_course.html .

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