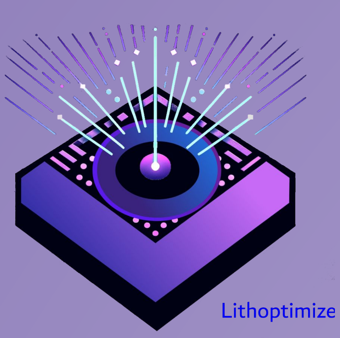

Intelligent Control for High-Performance EUV Lithography

Lithoptimize

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Background

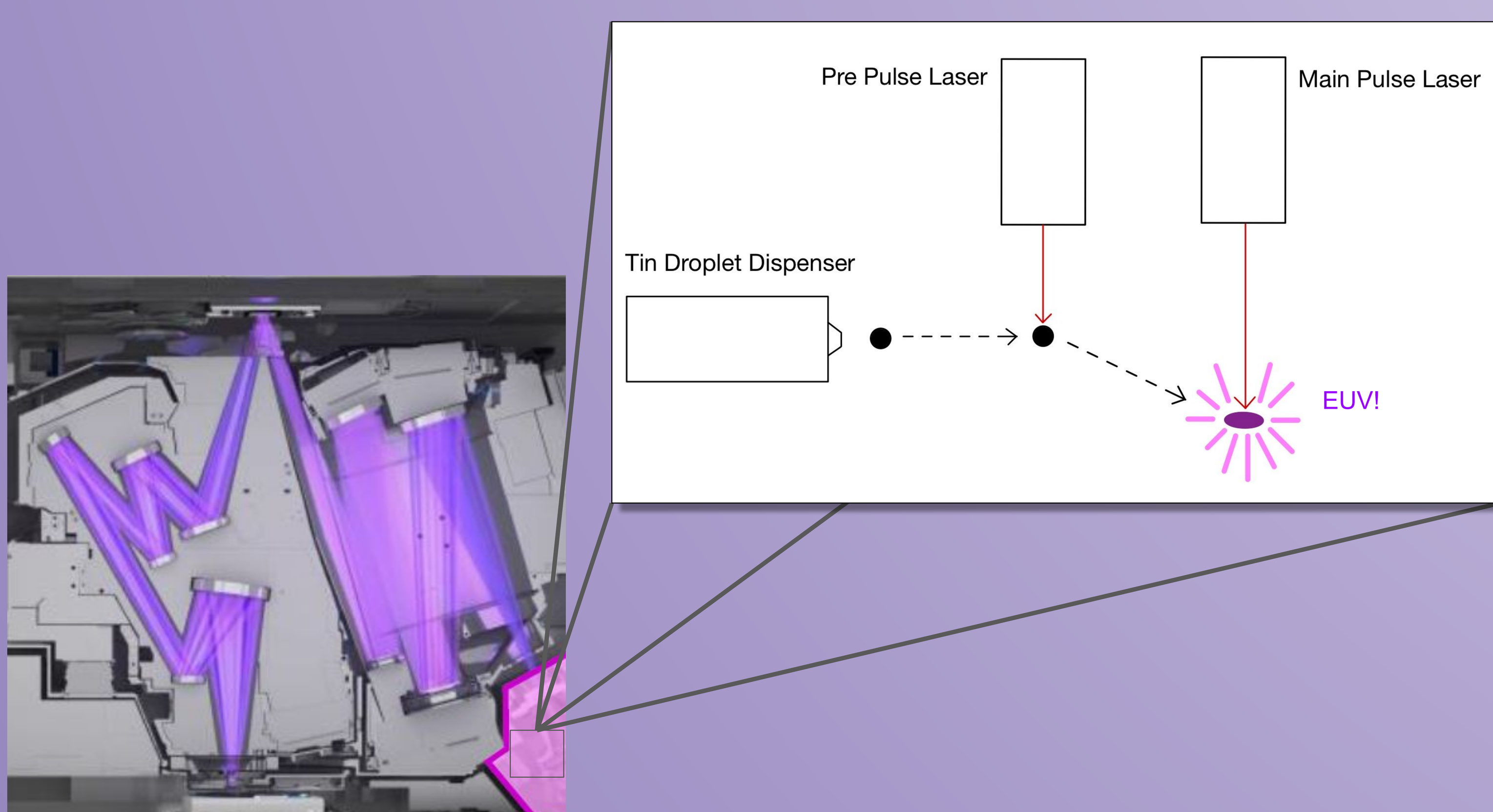
Current demands in semiconductor manufacturing requires reducing feature sizes to pack more processing power into each chip. To achieve this, ASML uses Extreme Ultraviolet light (EUV) in their photolithography machines to produce chips with features as small as 3 nanometers. Lithoptimize seeks to improve the efficiency of these photolithography machines by introducing advanced control algorithms that will help to increase both the quality and quantity of EUV produced by these machines.

Design Specification

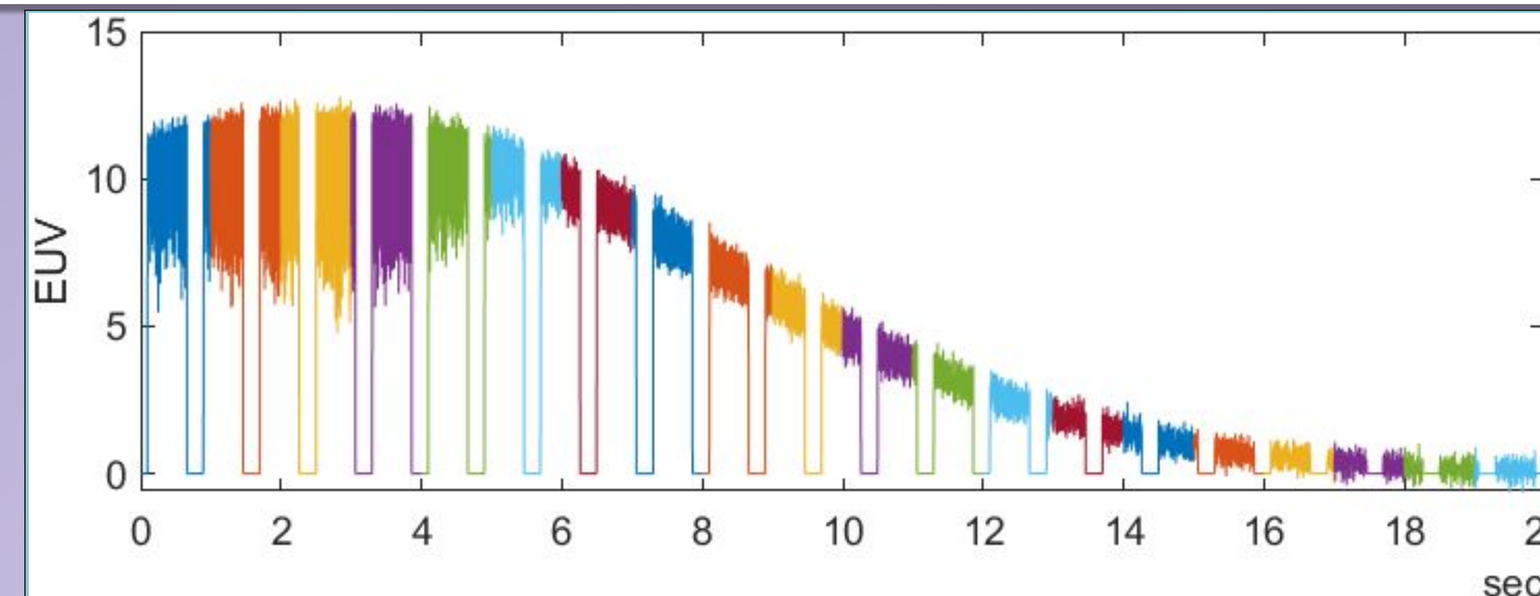
In order to improve the quantity and quality of EUV production, we needed to find a control structure capable of delivering high levels of EUV as well as making sure that the EUV levels vary at a rate of less than 1%. We explored several types of control algorithms, and finally settled on real-time bayesian optimization, which dealt with issues, including random noise, system drift, and output consistency while retaining a high level of EUV production.

System drift renders ineffective/suboptimal traditional optimization methods like coordinate, making it the major challenge to system operation that Bayesian optimization resolves.

EUV Production

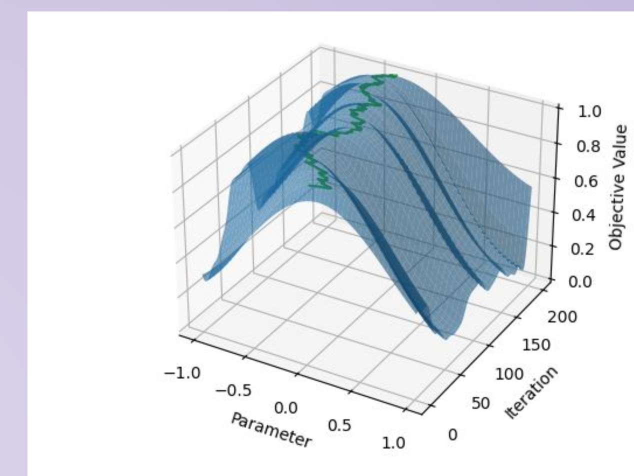


System Drift

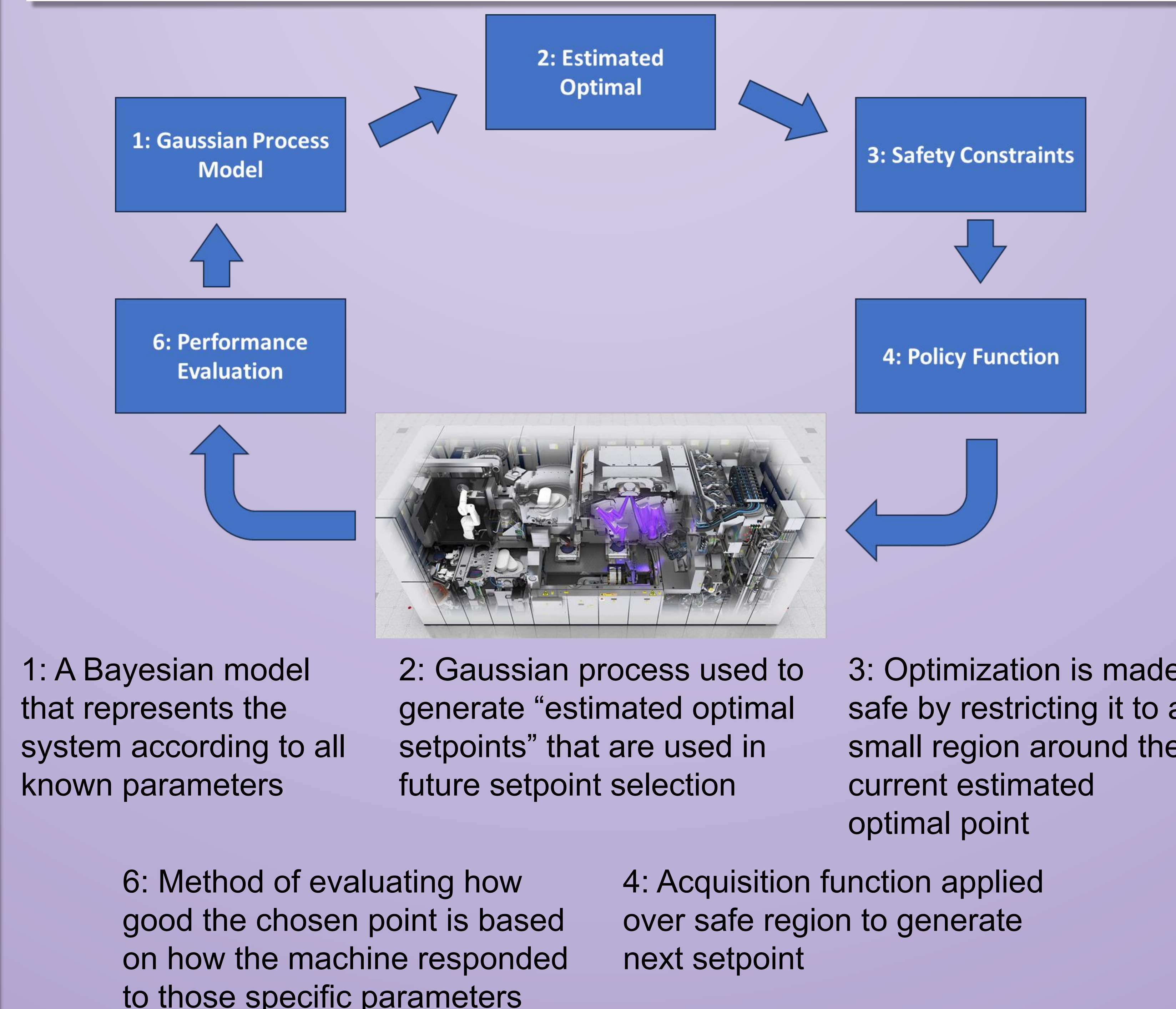


System performance under drift; performance degrades without controlled running (drift faster here than real system)

Gaussian Process (GP) model (right) encodes the expected EUV (or alternative "goal" function) as a function of the parameter space and time. We visualize the optimal as a time series (green) for this example 1D GP model



Final System Design



1: A Bayesian model that represents the system according to all known parameters

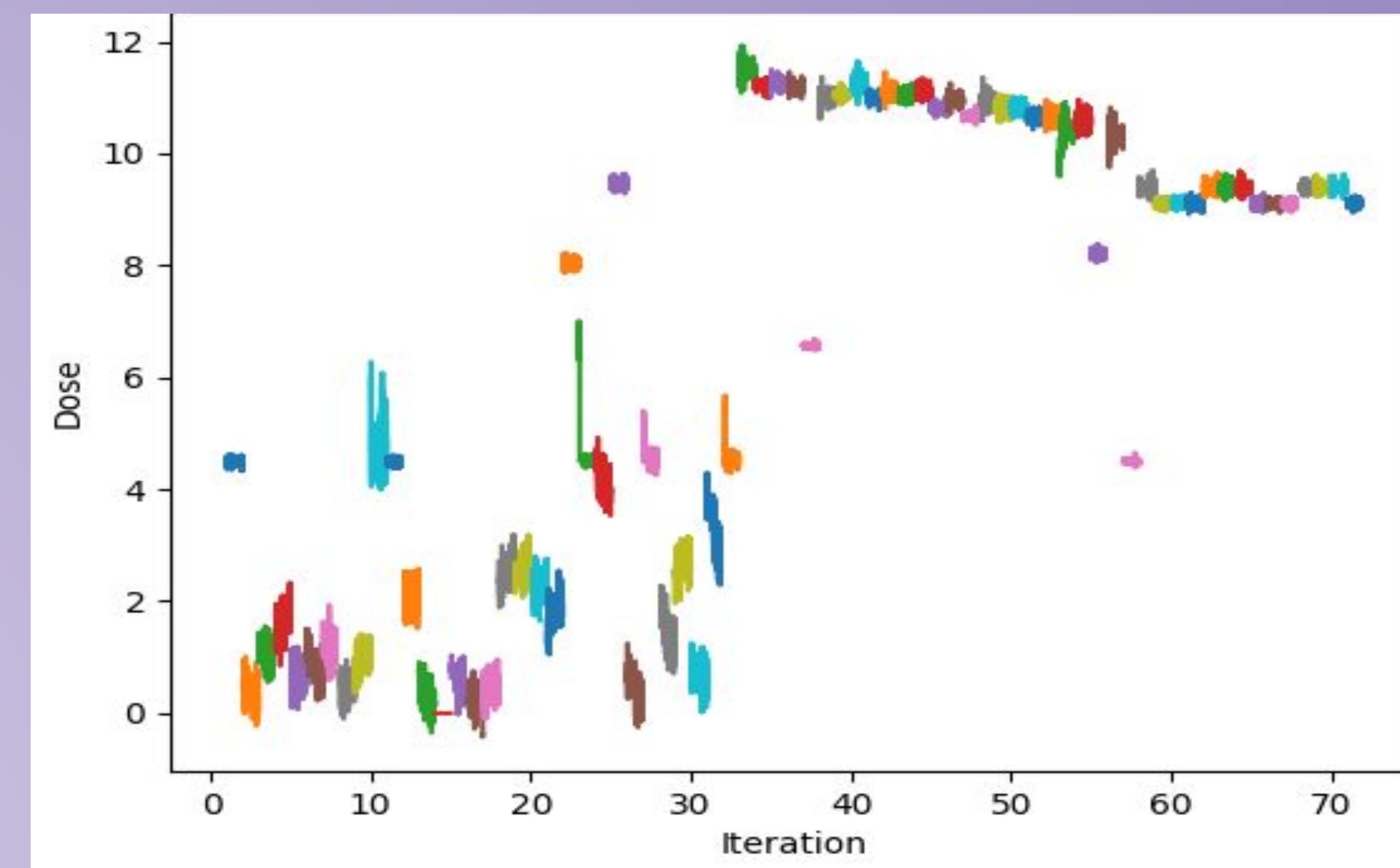
2: Gaussian process used to generate "estimated optimal setpoints" that are used in future setpoint selection

3: Optimization is made safe by restricting it to a small region around the current estimated optimal point

4: Acquisition function applied over safe region to generate next setpoint

6: Method of evaluating how good the chosen point is based on how the machine responded to those specific parameters

System Results



Operation divided into a learning phase with high exploration bias followed by real-time operation under drift conditions using a high exploitation bias to ensure safety. With a sufficiently detailed prior model, we found our system was able to track the optimal setpoint. A faster drift rate negatively impacted our performance during testing, seen in the tailing off of dose levels at the end of this example run.

Key Result #2 / References / Conclusions

Undecided Image.

Describe key result (consider bullet point list).

Acknowledgements:

We would like to thank our ASML mentor Dr. Andrew Liu, Prof. Ilan Ben-Yaacov, and Philippe Rerolle for their active roles in mentoring our team.

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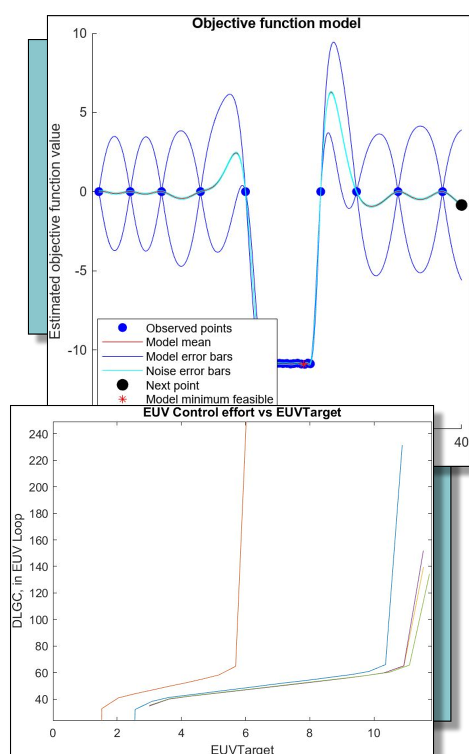
putting random stuff here for later use



Gaussian Process Model
A Bayesian model that represents the system according to all

Setpoint Evaluation
Online learning with safety means we needed to redefine how we evaluate setpoint performance, since output variations are suppressed.

Picture: Key Comp #3

Closed Loop EUV Controller
Real-time optimization was possible using a closed loop response for the Main Laser.

Picture: Key Comp #4

Safety Constraints
We make Bayesian optimization safe by restricting it to a small rectangular region around the current estimated optimal point