Inline Maximization of EUV Power

UCSB Senior Year Capstone Project with ASML

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Project description: Design or train a maximization method that that adjusts 7 knobs and can run forever and inline on the Extreme Ultra-Violet (EUV) light source to maximize the EUV power output. As part of the design process, survey and compare well-known methods from different fields in Machine Learning (ML) research, for example the Bayesian Optimization (BO) and Reinforcement Learning (RL) methods, and determine the best algorithm or agent that adjusts 7 setpoints and achieves the highest EUV power within given constraints and keeps the light source operating at optimum during drift and changes after service actions.

Background: ASML is the only company in the world that produces EUV machines. These machines etch very fine patterns onto silicon wafers, which is vitally important for the semiconductor industry to create smaller and more powerful computer chips. ASML's EUV machines are essential to producing high-end computer chips that are used by essentially every company involved in AI.

ASML San Diego, CA develops and supplies the critical EUV light source component. The light source uses LPP (Laser Produced Plasma) technology which takes place inside a large vacuum chamber by first shaping a ~30 micrometer tin (Sn) droplet with a laser pre-pulse and then converting the resulting tin disk (pancake) using a more powerful (tens of kW) main laser pulse to produce plasma and EUV light. This operation occurs at a rate of 50-60 kHz. Video 1 shows a behind-the-scenes tour of ASML San Diego, explaining the works and components of the EUV light sources. For this project, the highlight is 3:08 “Just blast tin with lasers” which shows the first pre-pulse hit of tin droplet to create tin disk and the second main pulse blast of tin disk to create EUV plasma. There are software adjustable knobs that influence the efficiency of EUV plasma generation. Currently, 7 of these setpoints are calibrated once during the installment of the machine. However, over time it is known these calibrated setpoints are known not to give best EUV power output possible, because of for example drift and service action. If optimized inline, the EUV light source could generate many more wafers for out costumers.

Problem Statement: For this project, a black-box model will be provided with the 7 setpoints as input and returns EUV power and other relevant signals to satisfy constraints. These will include for example the laser actuator signals, and measurement signals like the extracted target angle metrics from the tin target images, and the EUV power obtained. The model includes a state to simulate the dynamics of slow drift and abrupt changes of service actions. It has a seed input as well to mimic the setpoint variations among the different light sources in the fleet. The project should aim to achieve an algorithm or agent that adjusts 7 setpoints and achieves the highest EUV power within given constraints and keeps the light source operating at maximum during drift and changes after service actions. The project should aim to achieve the following:

- Explore and compare a variety of methods and tools for maximization, for example
    - Bayesian Optimization
    - Reinforcement Learning (Figure 2)
- Design optimization methods or train an online agents and determine their performance.
    - Evaluate EUV tracking performance on sufficient large fleet of sources (~100)
    - Evaluate satisfaction of the constraints, especially die yield performance constraint
- Make a recommendation for the preferred architecture and to fine-tune its performance.
    - Define architecture for the selected methods
    - Report used optimization algorithm and settings

To achieve this, the ideal "inline" maximization method should take into account the following:

- Deal with stochastic characteristics of EUV measurement: EUV signal contain significant measurement noise and the typical gradient optimization methods fail to converge.
- Multidimensional with coupling, non-linear and likely non-convex problem
- Satisfy non-linear (both equality and inequality) constraints: There are both hard safety constraints and soft yield performance constraints, for example using "Safe" Bayesian Optimization methods, like SafeOpt [3] and [4].
- Limit computational effort: Gaussian processes model complexity grow cubic with the number of sample points. Investigate approximations or alternatives, like Bayesian Neural Networks [1].
- Track drift: EUV optimum drifts over time due for example cold to hot transitions. Explore and investigate improvements to dynamically track the drift, like Dynamics Gaussian Process models [2].
- Avoid intrusive setpoints: Avoid the evaluation of setpoints that can lead to large EUV drops

References:

[1] A Study of Bayesian Neural Network Surrogates for Bayesian Optimization, Yucen Lily
[2] Bayesian Optimization for Dynamic Problems, Nyikosa F.M.,
[3] Efficient safe learning for controller tuning with experimental validation, Martha Zagorowska
[4] Bayesian Optimization with Safety Constraints: Safe and Automatic Parameter Tuning in Robotics, F. Berkenkamp

Further information:

https://en.wikipedia.org/wiki/Extreme_ultraviolet_lithography
https://www.asml.com/en/technology#lithography
Laser and tin in the light source - ASML - YouTube
The full EUV optical light path - ASML - YouTube
The reticle and reticle stage - ASML - YouTube
How An EUV Light Source Works - YouTube

Video 1: You Didn't Build your PC... This Did. - ASML Cymer Tour

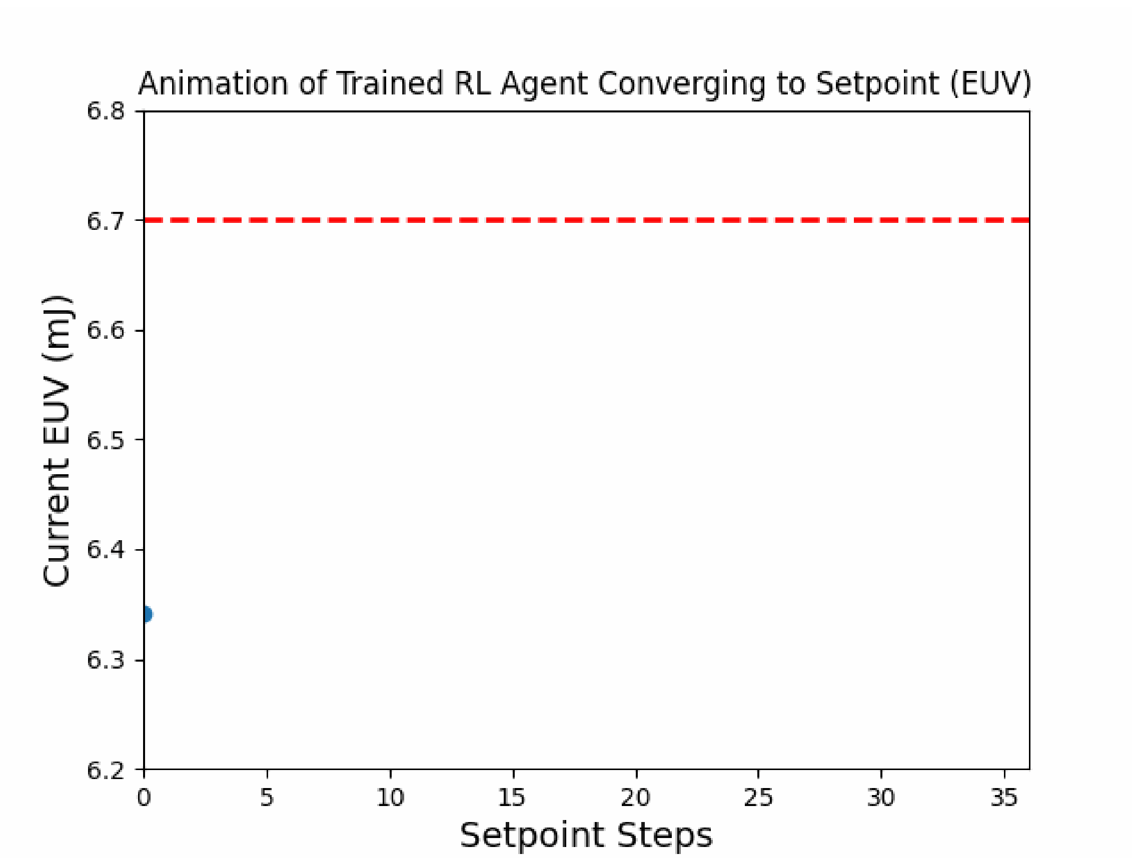

Figure 2: Reinforcement Learning