

GenAI-Driven EUV Power Maximization

UCSB Senior Year Capstone Project with ASML

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Project description: This project explores how Generative AI can help maximize Extreme Ultraviolet (EUV) light-source power with fewer experiments. Students will develop and evaluate an optimization approach that combines Bayesian Optimization (BO) with modern Tabular Foundation Models (TFMs), such as TabPFN [1], TabFM [2], and TabICL [3]. The optimization problem uses 7 adjustable source setpoints as inputs and measured EUV power as the main output. Similar to how Large Language Models (LLMs), such as ChatGPT, learn general patterns from large collections of text, TFMs learn patterns from spreadsheet-like data and can apply that knowledge to new tabular prediction tasks. In this project, the table contains plasma-control settings, and EUV power measurements. Students will investigate whether pretrained TFMs can improve BO by acting as fast surrogate models, uncertainty estimators, candidate-ranking tools, candidate filters, or warm-start models. The goal is to determine whether high EUV power can be reached with fewer measurements than traditional models trained only on data from the current experiment.

Background: ASML produces EUV lithography machines, which are essential for manufacturing advanced semiconductor chips [4]. ASML San Diego [5] develops the EUV light source, where laser-produced plasma (LPP) technology converts tin droplets into EUV light inside a vacuum chamber. In the source, a pre-pulse shapes a ~ 30 micrometer tin droplet into a disk, after which a high-power main pulse creates plasma and EUV light at 50–60 kHz. Several software-adjustable setpoints influence plasma-generation efficiency and are currently calibrated during installation. Better optimization could increase EUV power and improve wafer throughput for customers.

Problem Statement: Students will receive a black-box simulation model that takes 7 setpoints as input and returns EUV power plus relevant constraint and diagnostic signals. The simulator includes a seed input to represent variation across a fleet of light sources. Students will build an optimization workflow that uses TFMs with BO to recommend new setpoints, maximize EUV power, and satisfy operational constraints.

- Assess whether TFMs provide useful predictions, uncertainty estimates, rankings, or candidate filters for EUV optimization.
- Design BO workflows that use TFM surrogates and takes into account the following.
 - **Small-data learning:** Each candidate setpoint requires machine time, so the optimizer must be sample-efficient.
 - **Noisy measurements:** EUV power measurements contain stochastic variation, so real improvements must be separated from noise.
 - **Coupled nonlinear inputs:** The 7 setpoints form a multidimensional, nonlinear, and likely non-convex problem.

- **Constraint handling:** The method must respect hard safety limits and soft yield-performance constraints.
- Evaluate EUV improvement and constraint satisfaction across a simulated fleet of sources.
- Recommend the most promising models and report final choices, settings, and trade-offs.
- Investigate runtime, memory, GPU/CPU, and deployment requirements for embedding the selected TFM-assisted optimizer in the EUV source workflow.

The GenAI-driven EUV power maximization method should address the following success criteria:

- **Measurement efficiency:** Demonstrate a clear reduction in the number of optimization iterations or measurements required to reach the best achievable EUV power compared with a classical Gaussian-process BO baseline.
- **Fleet learning:** Show that performance improves as historical data from an increasing fleet of source instances is added, including better warm starts, faster convergence.
- **EUV power gain:** Achieve equal or higher final EUV power than the baseline while satisfying all hard operational limits and relevant soft constraints.
- **Robustness:** Maintain stable performance across different simulator seeds, source-to-source variation, noisy measurements, and constrained operating regions.
- **Deployment feasibility:** Quantify hardware requirements, including CPU/GPU needs, memory footprint, inference latency, model size, and integration trade-offs for embedding the optimizer in the source control environment.

Selected references and resources:

- [1] TabPFN: Accurate predictions on small data with a tabular foundation model, Nature, 2025.
 [2] TabFM: A zero-shot foundation model for tabular data, Google Research, 2026.
 [3] TabICL: A Tabular Foundation Model for In-Context Learning on Large Data, ICML, 2025.
 [4] [The World's Most Important Machine](#) - Veritasium
 [5] [You Didn't Build your PC... This Did. - ASML Cymer Tour](#)

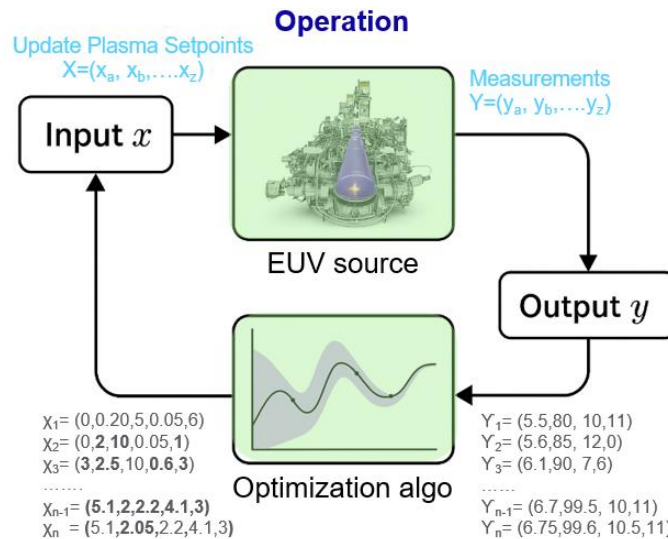


Figure 1: Principles of Operation for GenAI-Driven EUV Power Maximization