Parameter Operated Geometric Optimizer for EUV Generation

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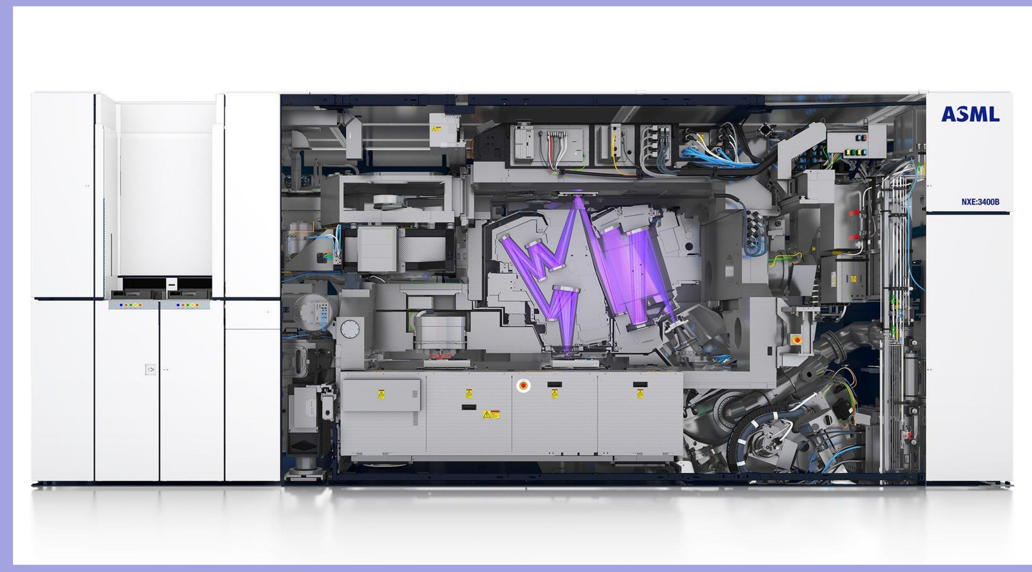
Background

ASML is the sole provider of **extreme ultraviolet (EUV) lithography machines**, which enable the fabrication of cutting-edge silicon devices. These machines generate EUV light by flattening droplets of tin into tin targets and subsequently evaporating them. The shape of these targets is potentially correlated with the amount of EUV emitted.

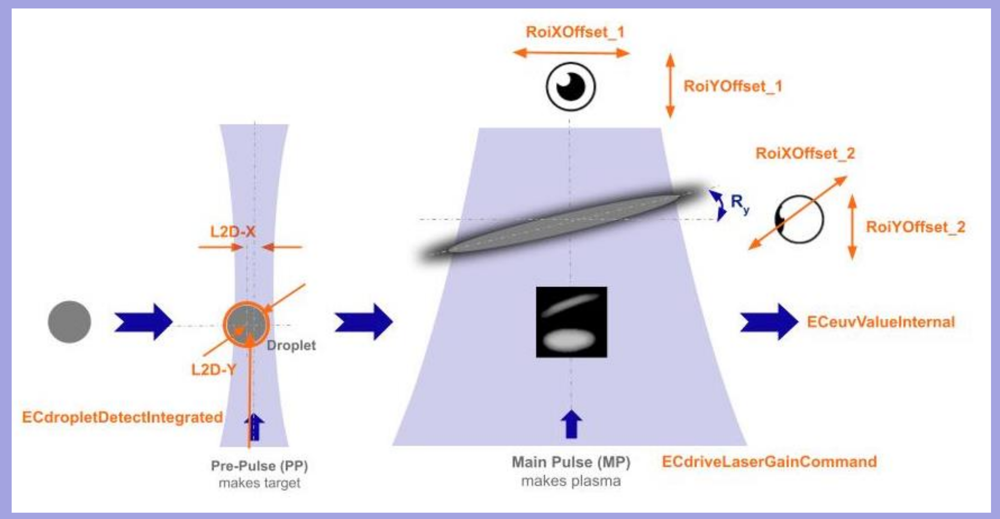


ASML Photolithography Machine

Problem Statement

Internal machine parameters like laser strength and beam offset affect tin target shape, but high operational costs limit direct testing.

Due to high operational costs, direct experimentation on these machines is limited.



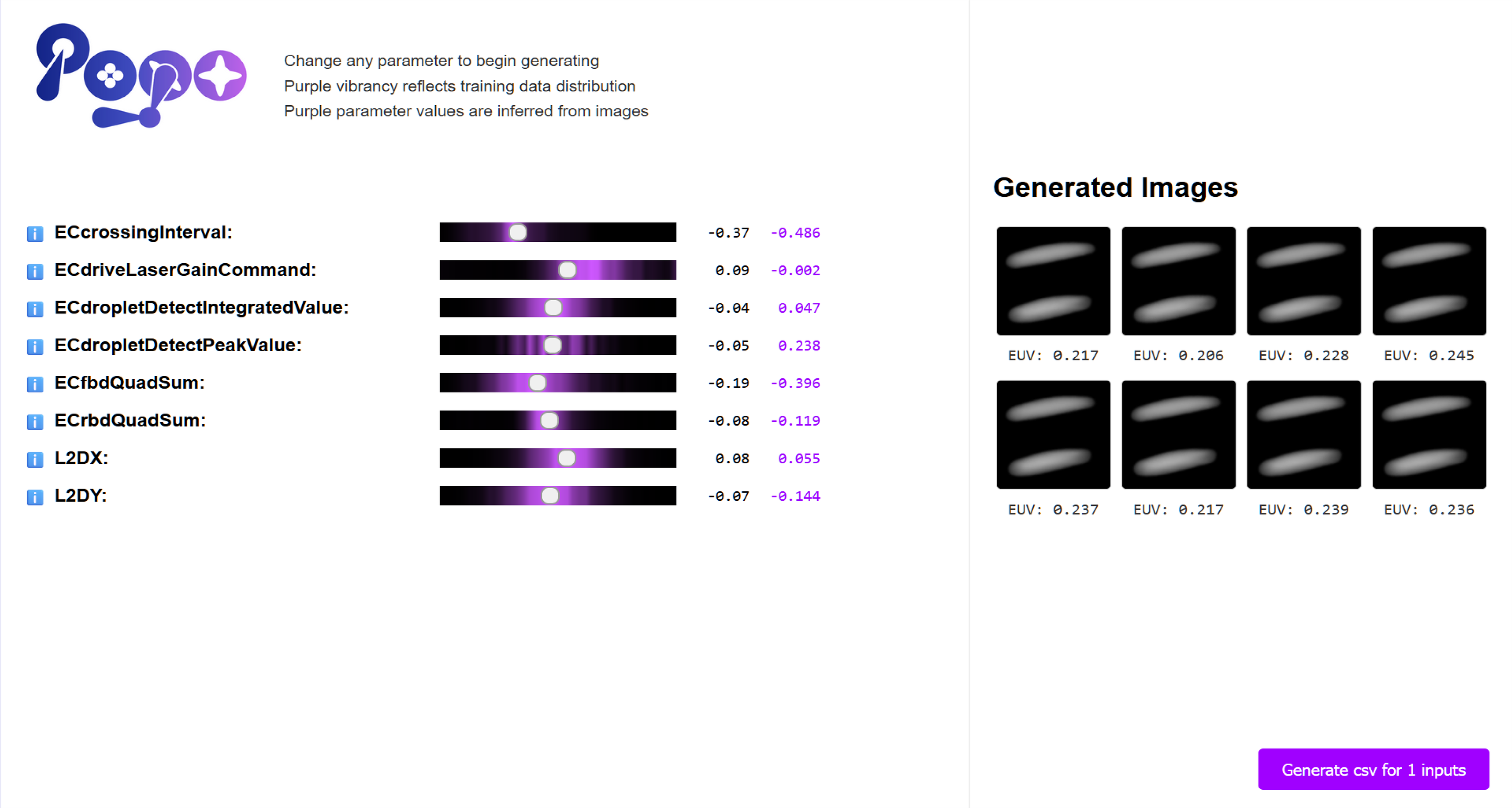
EUV machine parameters & variables

To address this, we developed **POGO** *(Parameter Operated Geometric Optimizer)*, a web tool that:

- Generates images of tin targets from user-defined machine parameters
- Estimates EUV yield and other parameters from images of tin targets

POGO thus enables quick, cost-efficient testing and optimization with direct machine access.

POGO User Interface

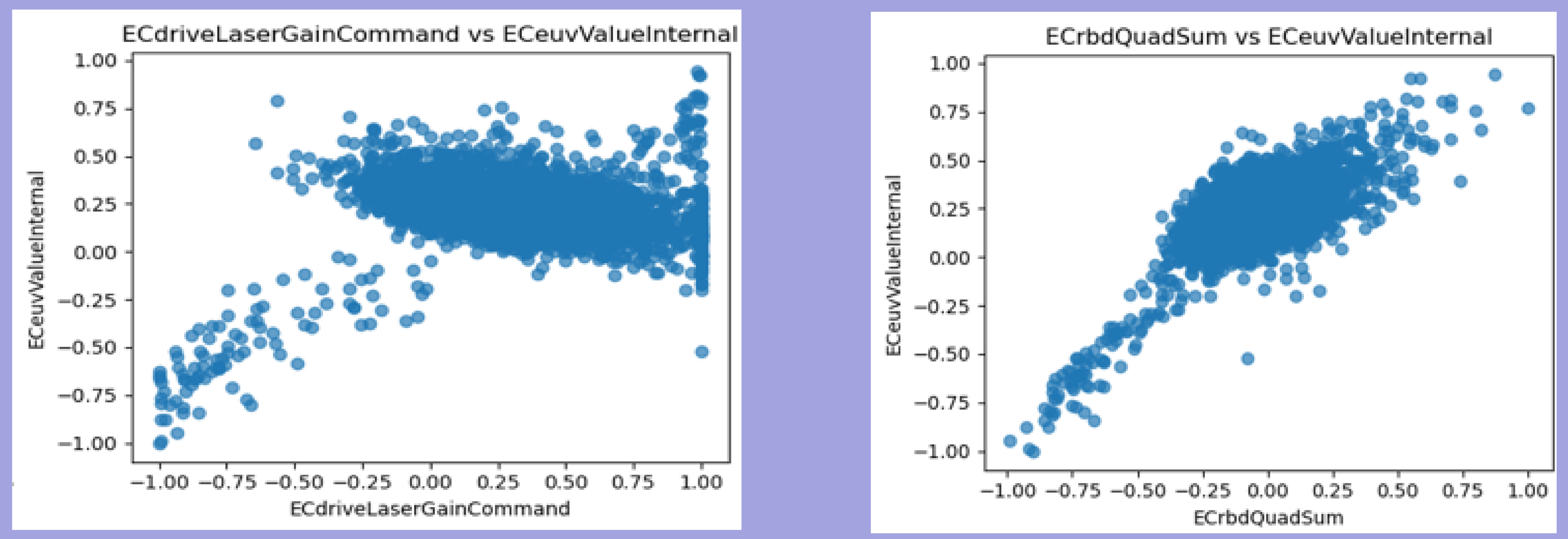


POGO Web Tool

The POGO web tool allows users to generate images of tin targets (right) by specifying EUV machine parameters (left).

POGO also predicts dependent parameters and metrics, such as EUV yield and positional offset.

Results and Findings



EUV Yield vs. Drive Laser (left) and EUV Yield vs. QuadSum (right)

In order to determine which lithography machine parameters maximized EUV yield, we used both linear and nonlinear regression models to find correlations in the data. Results indicate 'QuadSum' and 'DriveLaser' have strong positive correlation with EUV yield, both of which are parameters related to the laser. Furthermore, we also found that the EUV output is directly correlated with the size of the target.

AI Models Used for Target Generation

Variational Autoencoder (VAE)

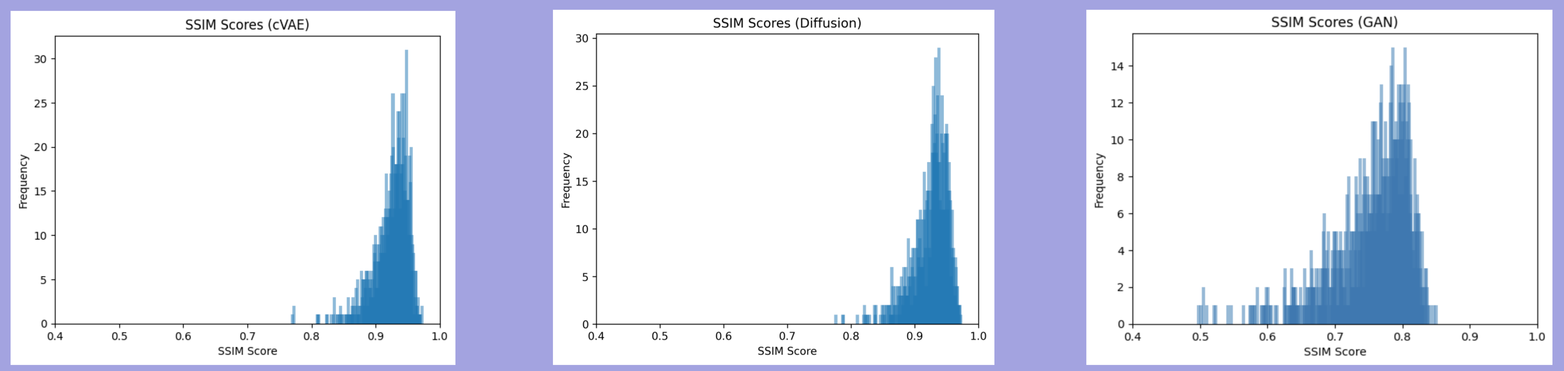
The VAE architecture relies on two networks, an Encoder and a Decoder. The Encoder network compresses images down to a smaller representation, and the Decoder then tries to reconstruct the original image. After training, the Decoder can be used to generate images. The VAE proved to be the fastest model.

Diffusion Model

The Diffusion architecture learns to turn noise into coherent images. Training images are intentionally "corrupted," and the model learns to undo the corruption. Eventually the model can turn a completely noisy or corrupted image into a clear and sharp one. The Diffusion model had the highest reconstruction accuracy.

Generative Adversarial Network (GAN)

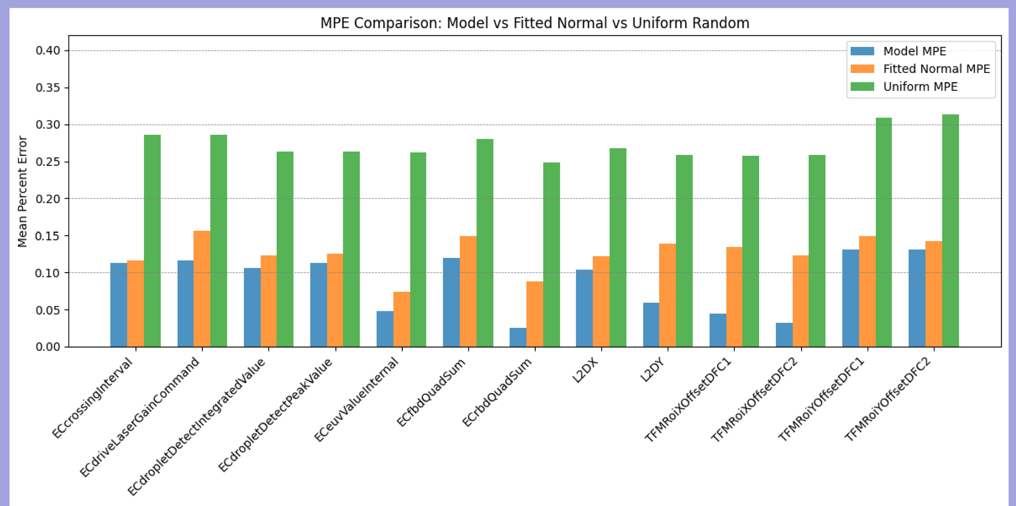
The GAN model consists of two separate, competing models; The Generator tries to create realistic images, while the Discriminator gives feedback to the Generator so that it can improve. This architecture is difficult to train due to the presence of two models, and requires more work to be suitable for tin target generation.



Reconstruction accuracy of generative models VAE (left), Diffusion (middle), and GAN (right)

img2par

The img2par model predicts EUV yield and machine parameters from images of tin targets. The model was adapted from the Encoder architecture of the VAE, and consists of convolutional and fully connected layers.



Img2par parameter estimation error (blue) compared to uniform sampling(green), and fitted Gaussian sampling (orange)

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