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Optimization of Silicon Photonic Components using Multi-Fidelity Simulations and Co-Kriging

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Silicon photonic devices can be very compact because of the high refractive index contrast. But this also makes them very sensitive to geometry variations, and hard to model [1]. Typically, a fully vectorial, 3D solution of Maxwell's equations is the only reliable simulation technique, be it with *eigenmode expansion* (EME) or *finite-difference-time-domain* (FDTD). Finding an optimum geometry of a parametric component is therefore computationally very expensive, and it is important to keep the number of these 'expensive' simulation as small as possible. *Efficient global optimization* (EGO) uses *Kriging* to reduce the number of simulations by adaptively selecting the simulation point with the largest likelyhood of producing a better component. However, individual simulations are still expensive.

In this work, we combine expensive, high-precision 3D-FDTD simulations with much cheaper, lower-precision 2D EME simulations to accelerate the optimization. This *Co-Kriging* technique uses the cheap simulations to learn the trends of the component behavior, which are calibrated with the expensive simulations [2]. The cheap simulations allow a quick building of the landscape of multi-dimensional parameter space, which minimized the use of the expensive simulations.

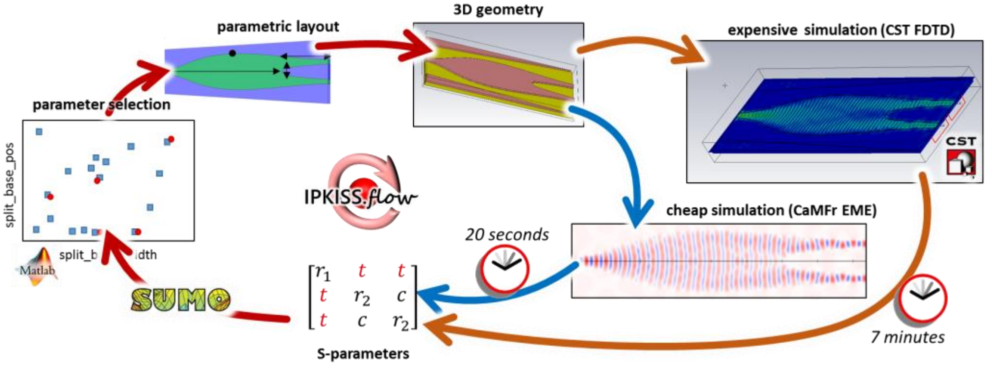

Fig. 1. Optimization of a photonic component using cheap and expensive simulations

We have optimized the geometry of a silicon 1×2 splitter for maximum transmission over the entire wavelength range 1.5-1.6µm. The splitter is a parametric component in the IPKISS design framework, and has 5 parameters for the smooth shape shown in Fig. 2. We defined 2 simulation strategies: a fast 2D EME simulation in CaMFr, and an accurate 3D-FDTD simulation in CST Studio. Both simulations are launched from the IPKISS python interface [3]. The CoKriging optimization is controlled by the *SUMO* and *ooDACE* toolboxes for Matlab [4,5].

The results of this optimization is shown in Fig. 2. The exploration starts with a Latin hypercube sampling of the parameter space using 21 cheap and 4 expensive simulations. After this initial mapping, the cheap simulations are used to map the landscape of the transmission over the entire parameter space, while the expensive simulations are used to target the optimum. The total global optimization in 5 dimensions uses 238 cheap simulations (75 minutes) and only 12 expensive simulations (94 minutes) and yields a splitter with a transmission > 87% over the entire wavelength range.

This demonstrates that the combination of simulation techniques with different fidelity and an efficient adaptive sampling algorithms can dramatically improve the optimization cycle of high-contrast photonic components.

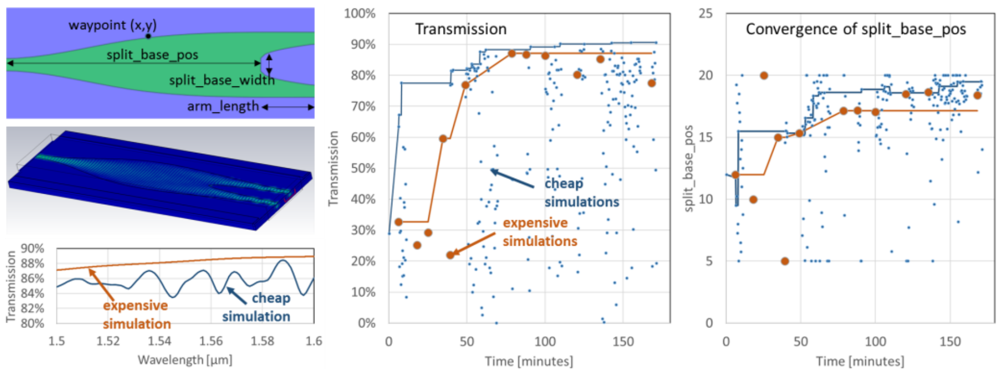

Fig. 2. Optimization of a 1×2 splitter. Left: splitter geometry and simulation of the optimum result. Middle: Evolution of transmission in cheap and expensive simulations. Right. Sampling of one parameter during simulations.

References

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