Time-Efficient Photonic Variability Simulator for Uncertainty Quantification of Photonic Integrated Circuit

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***Abstract* - We present a novel simulation platform for uncertainty quantification (UQ) studies of photonic integrated circuit (PIC) design. This platform supports time-efficient variability studies such as stochastic collocation and spectral projection that enables variability aware PIC design.**

I. Introduction

As the density of optical components in photonic integrated circuits (PICs) rises, rigorous simulation and extensive characterization are required for complicated designs such as interleavers and optical switches with a large radix before fabrication. Even though the physical layer effects can be accurately captured through advanced modeling techniques, the variability of fabrication can significantly degrade the system performance (e.g. insertion loss, crosstalk, etc.) and impact the product yield. This is due to the high refractive index contrast in silicon photonics, where nanometer-scale deviations are crucial for the overall performance of photonic devices [1-2]. Consequently, rigorous studies of uncertainty quantification (UQ) of dense PIC structures are essential in the fabless design process prior to foundry fabrication processes.

Over the past decade, several UQ techniques have been demonstrated to assess device-level variation [3-4]. Among the popular choices for stochastic simulations, Monte Carlo is one of the most straightforward techniques to apply random variation on model parameters, while the underlying physics of a photonic simulator remains uninterrupted [5]. Even though brute-force Monte Carlo simulations offer a great accuracy, these simulations in general are too computationally intensive. The Monte Carlo convergence rate is generally far too slow to simulate dense PICs with parameters varied through the fabrication process. As an alternative, polynomial chaos expansion offers more efficient simulations compared to Monte Carlo method, by mathematically modeling the stochastic processes i.e. the system performance metrics [6]. Computing the stochastic moments from this model can provide a massive speedup to the calculation of mean and variance compared to Monte Carlo (the mathematical reasoning behind the speedup has been thoroughly discussed in the literature [7]), but polynomial chaos has a larger computational cost when the numbers of random variables increases. Thus, it is important to know at which when polynomial chaos expansion yields faster convergence than Monte Carlo techniques, and which method best minimizes time spent in the design and simulation stage.

In this paper, we present our photonic variability simulator, a Python-based platform, to model the effects due to fabrication variations in PIC designs using both Monte Carlo and polynomial chaos expansion. A scalable and time efficient solution of advanced UQ is described based on the interaction between Chaospy [8] with OptSim, a simulation engine based on compact models of photonic components (S-matrix).

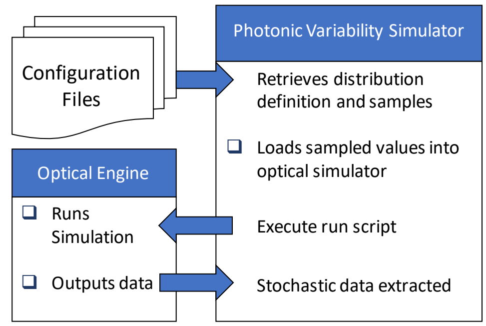

Fig. 1. Flowchart describing how our photonic variability simulator interacts with/controls the optical engine. The configuration file describes the Chaospy probability distribution of the parameter to be varied. The Python simulation environment will then randomly sample from the distribution and use the samples to populate the sim.

II. Photonic Variability Simulator

The photonic variability simulator we implemented is a simulation scheme that interfaces with Chaospy and the optical engine described in Fig. 1. A nonintrusive polynomial chaos model was employed, where the optical engine is treated as a black box. The inputs for optical engine are the randomly sampled component variables. The outputs of the various spectral and/or time domain data are then used to calculate the mean and variance of a parameter of interest, like the responsivity of a photodiode, or the Q factor of a ring. These statistical moments can be calculated by either Monte Carlo or polynomial chaos methods e.g. stochastic collocation or linear regression.

Simulation flexibility is derived from using Chaospy to both sample the variables and perform polynomial chaos expansion. The open-source package can support correlated stochastic models, user-defined algorithms for UQ, and an exhaustive library of pre-defined probability distributions. Using these capabilities allows for comparing UQ techniques while simulating dense PICs with large numbers of random variables.

This flow also offers a great deal of scalability in comparison to one based on intrusive polynomial chaos techniques. Intrusive polynomial chaos techniques involve changing the underlying equations of the simulation to include stochastic information inherently. Intrusive methods consequently yield statistical information about a figure of merit after one simulation. Both intrusive and nonintrusive polynomial chaos methods are valid, and simulation environments using intrusive techniques have been reported in

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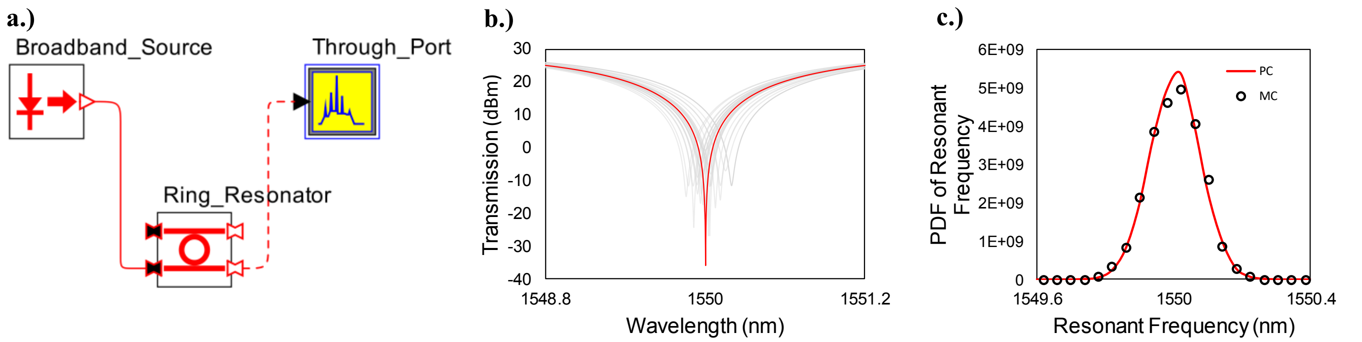

Fig. 2. (a) Optsim schematic for the test verifying the functionality of the Python environment for uncertainty quantification. (b) Results from Monte Carlo samples from the experiments. The red plot represents the mean; the gray represent various runs. (c) probability density function (PDF) of ring resonance. The red plot is the PDF taken from a polynomial chaos expansion model made after 30 runs, while the black markers were taken from the Monte Carlo PDF generated with 1000 samples.

other disciplines such as circuit design [9]. But due to the complexity of optical simulations, intrusive methods can be more computationally expensive to solve than the original problem or can cause modeling correlations between random variables to become more difficult [6]. Consequently, uncertainty analysis for PICs ideally leverage existing optical simulators to perform experiments and employ nonintrusive methods. Using a well-tested optical simulator allows for the greatest amount of flexibility and ensures a scalable methodology for larger, complex systems.

OptSim was chosen as the optical engine to perform the compact model circuit-level analysis. The authors want to note that our photonic variability simulator uses Chaospy to handle all stochastic processing. It is essentially independent of the optical engine underneath, and should be compatible with any kind of circuit-level simulator based on compact model S-matrix analysis.

III. Testing Simulation Environment

The experiment used to verify the Chaospy/OptSim design flow is described in Fig 2. A silicon-based add-drop ring resonator was simulated to operate at 1550 nm. The OptSim schematic is shown in Fig 2a. The geometric parameters of ring were modeled as Gaussian random variables. As the focus of the paper on the simulation methodology and not the variation data itself, the variations for all three values being chosen at relatively reasonable values according to current fabrication tolerances, as shown in Table 1. Various Monte Carlo runs are displayed in Fig. 2b, all directly taken from runs of the simulator. Fig. 2c. shows the generated probability density function from 1000 runs of Monte Carlo and 30 runs of polynomial chaos. The similarity in the distributions confirm the expected advantages of polynomial chaos for a small number of random variables, validating the Chaospy/OptSim integration.

IV. Conclusion

The photonic variation simulator we implemented provides a straightforward, scalable method to investigate the variation sensitivity of PIC designs for creating more robust integrated systems. The simulator supports both Monte Carlo and polynomial chaos analysis of integrated optical systems, allowing for comparisons between the two approaches for higher order stochastic simulations of PICs. With this capability, more in-depth investigations of device sensitivity can be conducted for high yield, first pass silicon designs.

Simulation Random Variables		
Parameter Name	**Mean**	**Std. Dev.**
Circumference (m)	4.22e-5	2e-9
Effective Index (N_{eff})	3.6730	1.65e-5
Tranmission Coefficients	0.5	1e-3

Table 1. Parameters used for simulations described in Fig. 2. All parameters were assumed to have a Normal distribution.

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