Dimensionality reduction for the on-chip integration of advanced photonic devices and functionalities

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Abstract *Design of modern photonic devices requires to handle a large number of parameters and figures of merit. By scaling down the complexity of the problem, machine learning dimensionality reduction enables the discovery of better performing devices, higher integration scale, and efficient evaluation of fabrication tolerances.*

Introduction

Integrated photonics aims at realizing on-chip a wide range of functionalities, including light generation and detection, coupling, routing, modulation, and filtering. As such, performance and scale of integration have always been a primary focus in the development of novel devices. Pursuing these goals, many traditional building blocks have been realized using relatively simple geometries whose performance are controlled by a small number of parameters that can be designed manually. However, this process results in relatively large devices, with dimensions of tens or even hundreds of microns even for the high index contrast silicon photonics platform. These limitations ignited a strong research interest in exploring more complex geometries, non-trivial shapes, and metamaterials, achieving unparalleled size reduction and innovative functionalities[1],[2]. Inevitably, this also imposed increasing challenges for classical design methods. Sweep of design parameters becomes computationally intractable or not applicable as parameters are often strongly correlated. Design trends and guidelines become difficult to extract, visualize or understand.

As a result, optimization methods are now commonly used to search more efficiently for high-performance designs with complex geometries. Likewise, machine learning approaches, particularly neural networks, have been more recently used to explore the ever expanding design space[3]–[5]. However, two main obstacles emerge in high-dimensional design problems. The high-dimensional design space is also commonly highly non-convex and identifying the global optimum with a reasonable confidence becomes challenging. In particular, the outcome of gradient-based optimization, e.g. those exploiting the adjoint method, is strongly dependent on the initial guess, with the risk of local, suboptimal solutions. Additionally, the design is often not only multi-parameter but also multi-objective since multiple performance and fabrication requirements need to be taken into account, making it difficult to craft appropriate objective functions which can lead to a device with the required performance. Lastly, only a single or a handful of optimized designs are often discovered, revealing very little on the characteristics of the design space and the influence of the design parameters on the device performance.

Here, we present our recent work on the use of dimensionality reduction and optimization tools to tackle some of the challenges in the analysis and design of multi-parameter, multi-objective photonic devices.

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Use of dimensionality reduction

A possible approach to handle high-dimensional design problems is to exploit the dependency existing between the parameters governing the device behavior to effectively reduce their number. Adapting dimensionality-reduction machine-learning algorithms, we have developed a design strategy[6], schematically represented in Fig. 1,

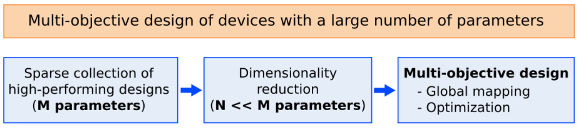

Fig. 1: The proposed strategy for multi-objective, multi-parameter photonic design.

that implements this approach. First, multiple iterations of a gradient-based optimization algorithm are used to generate a small collection of different good designs, i.e., designs that optimize a primary performance criterion (Fig. 1a). These optimizations involve the original M parameters. In the second stage, dimensionality reduction is applied to analyze the relationship in the parameter space between these designs. The goal is to identify a lower-dimensional sub-space of highly efficient designs. This sub-space is described by significantly fewer hyper-parameters compared with the original design space (N<<M). In the last stage, we introduce multiple design objectives. Depending on the number of hyper-parameters N, this can be achieved either by exhaustively mapping the design sub-space by computing across all required performance criteria or by exploiting a (multi-objective) optimization algorithm within the sub-space, which is commonly easier to explore compared to the original design space.

Application examples

This approach has been successfully applied to several design scenarios, including silicon-based vertical grating couplers[6], grating couplers incorporating subwavelength metamaterials for enlarged feature size[7]–[9], and power splitters[10].

Figure 2(a) shows the schematic layout of an integrated micro-antenna in the silicon-on-insulator (SOI) platform whose design has been optimized through global mapping of the design sub-space[11]. The antenna is based on a surface grating with unit cells composed by a 300-nm-thick pillar and an L-shape segment partially etched to 150 nm. The antenna has five periods of which the first one is apodized. The goal of the design is to maximize the fraction of optical power diffracted upwards while maintaining a vertical emission and low back-reflection into the input waveguide. The design requires the optimization of M=10 parameters representing the length of each segment in the two different periods. The use of the described design strategy (with principal component analysis as dimensionality reduction tool) reveals that it is possible to represent a good antenna design with high diffraction efficiency using only N=3 parameters instead of the original 10, allowing a rapid and exhaustive mapping of the region of good designs by parameter sweeps. This allows to identify a compact design with total grating length of 3.6 µm, whose performance is reported in Fig. 2(b). At the design wavelength of 1550 nm, the upward diffraction efficiency (blue solid line) has a maximum T_{up} = 0.88 (-0.55 dB). Despite the vertical emission, back-reflection remains below -17 dB across the entire 1450 -1650 nm band (orange solid line) and reaches -20 dB at 1550 nm.

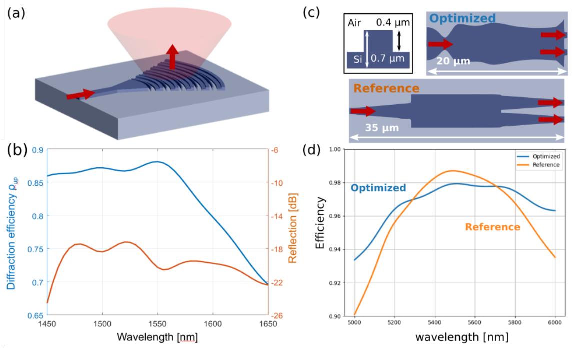

Fig. 2: (a) Schematic of the vertical micro-antenna for the near-IR wavelength range. (b) Diffraction efficiency and back-reflection of the optimized antenna. (c) Power splitter for the mid-IR wavelength range. The layout of the optimized design as well as that of a reference device are shown. (d) Wavelength dependence of the efficiency for the two devices.

Figure 2(c) shows a second device example whose design exploited instead an optimization algorithm running on the lower-dimensional design sub-space. The device is a power splitter for the mid-IR wavelength range realized on a rib-shaped silicon waveguide with thickness of 700 nm and a partial etch of 400 nm. The waveguide is suspended to avoid the large SiO_2 absorptions in this wavelength range[12]. A design obtained with a 1x2 MMI is used as reference (marked as “reference” in the figure). Input and output waveguides are 1.5 µm wide and tapers are used to enlarge their width up to 3.5 µm. The MMI is 8 µm wide and 15 µm long. The design objective is to optimize the profile of the device in order to make it more compact without severely hampering its performance in terms of efficiency, bandwidth, and back-reflections. The profile of the device is symmetrical and is sampled using 16 points whose coordinates represent the M = 16 parameters describing the device. To generate the layout, a segmented linear interpolation is performed between the 16 points. Sharp features are removed by convolution with a Gaussian function. The length of the device is fixed at 20 µm and 1.5 µm-wide input/output waveguides are

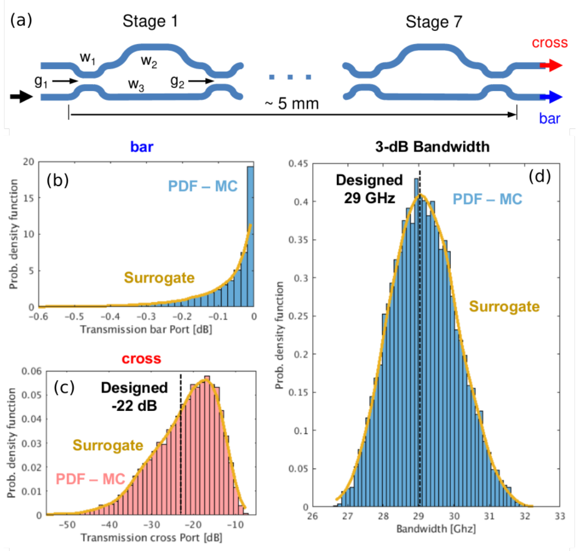

Fig. 3: (a) Schematic of the cascaded Mach-Zehnder filter. Probability density functions of the transmission at bar (b) and cross (c) ports as well bandwidth (d) are computed with a polynomial chaos surrogate model and dimensionality reduction and compared with reference Monte Carlo analysis.

interfaced directly to the device, without tapers. The described design procedure allows to reduce the initial 16 parameters to 7 hyper-parameters. The resulting dimensionality of the sub-space still makes global mapping impractical in this case. A multi-objective genetic algorithm[13] is exploited instead to navigate this sub-space and simultaneously maximize the device efficiency and bandwidth and minimize back-reflections. The final design profile is marked in Fig. 2(c) as “optimized”. Efficiency comparison for the reference and optimized devices is reported in Fig. 2(d). Despite a 40% reduction in length, the optimized design has an efficiency reduction of less than 1% at λ = 5.5 µm. The optimized design also shows a reduced roll-off, especially in the 5.2 - 5.8 µm range. Reflections are comparable between the two designs.

Fabrication tolerance analysis

The analysis of performance variation due to fabrication tolerance is a fundamental aspect in the design of a photonic component. Yet this analysis is often complicated by the stochastic nature of the tolerance and by the presence of a large number of parameters that can suffer fabrication-related deviations. Recently, we proposed an approach that can largely reduce the computational resources required for the analysis by combining sparse polynomial chaos surrogate models with dimensionality reduction[14]. First, Karhunen-Loève transform is used to both reduce the number of input parameters and remove their correlation, similarly to the approach shown in Fig. 1. Additionally, principal component analysis is applied also to the output variables to achieve the same result, i.e., reduce their number exploiting their inherit correlation.

A seven-order Mach-Zehnder filter used as example is shown in Fig. 3(a)[14]. The filter is designed to have a nominal 3-dB bandwidth of 29 GHz at a wavelength of 1522 nm, an in-band isolation larger than 20 dB, and a free spectral range of 100 GHz. The estimated total filter length once realized on a SOI technology is about 5 mm. Uncertainty is considered in the width and thickness of the waveguides and the separating gaps in the directional couplers. The total number of uncertain parameter is M=38, all assumed to be Gaussian distributed parameters. We also assume the parameters as correlated with a correlation length of 4.5 mm. The output variables of the analysis are 1000 wavelength samples of the simulated transfer function of the filter. The impact of the uncertainties on the filter transfer function can be analyzed by a standard Monte Carlo analysis, which would require about 10^4 simulations to assure convergence. For this example, the proposed technique allows to reduce the number of input random parameter to only N=9 from the original 38 and also compress the output to 9 principal components from the original 1000. In this way, the full stochastic analysis can be performed with only 200 simulations, with a 30-fold reduction in computational time compared to Monte Carlo. The probability density function of the transmission at the bar and cross port for the central wavelength and the 3-dB bandwidth are presented in Fig. 3(b-d), respectively, showing an excellent agreement.

Conclusion

Design of photonic devices is rapidly growing in complexity, both in terms of the number of parameters that need to be handled as well as for the multiple figures of merit to be simultaneously optimized. Some of these quantities, e.g., fabrication tolerance, are particularly complex to include in the design process because their evaluation could require large computational resources. Machine learning and in particular dimensionality reduction can provide a powerful approach to scale down the complexity of the analysis and design problem, enabling the discovery of better performing, robust, and compact photonic devices and the on-chip integration of novel functionalities.

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