Machine Learning Aided Prediction of Fabrication Uncertainties in Integrated Multi-Ring Filters

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Abstract: We propose a machine learning-based framework to predict the fabrication uncertainty and evaluate the effective-index shift in multi-ring integrated filtering elements. Excellent results are achieved in predicting each ring's effective-index shift.

1. Introduction

Photonic integrated circuits (PICs) are becoming increasingly present in the literature as competitive solutions for switching and filtering in transparent optical applications. PICs can offer several benefits in terms of mass production capability and cost-effectiveness while simultaneously allowing a significant degree of freedom in design and control strategies. In this context, while many passive devices can be reliably manufactured under reasonable fabrication tolerances, certain components are still severely affected by tolerances, requiring complex and resource-consuming tuning schemes to ensure the appropriate behavior [1]. One such component is the Micro-Ring Resonator (MRR), which is one of the standard building blocks for photonic switches and filters. Typically the single-ring configurations can be easily tuned, while its cascaded and more advanced configurations do not allow a straightforward and simple solution.

In this context, we proposed a Machine leaning (ML) based approach to predict the fabrication uncertainty and evaluate the effective-index shift in multi-ring integrated filtering elements in order to achieve an optimized tuning configuration. The training dataset for this approach is comprised of the frequency response (phase and amplitude), which is generated using an analytical model for a two-stage ladder MRR filter. The proposed ML model is exploited to achieve an optimized tuning configuration by predicting the effective-index shift of each ring in real-time operation which is traditionally time-consuming and requires a significant effort for an optimized tuning.

2. MRR Filter and Dataset Generation

The device under analysis consists of a two-stage ladder MRR filter [2], depicted in Fig. 1a. This higher-order filtering element is suited for optical Wavelength-Division Multiplexing (WDM) applications, as it allows flat-top transmission, steep stop-band transition, and large Free-spectral ranges (FSR), as shown in Fig. 1b. In addition to this, the device under analysis is a perfect solution for Wavelength-Selective Switching (WSS) [3], proper tuning remains a fundamental issue for real implementations. Due to the high effective-index sensitivity of resonance-based elements, even small fabrication non-idealities can lead to severe transmission impairments without proper tuning. Furthermore, an asymmetric variation of the index in different rings may lead to severe distortions on top of a general resonant frequency shift.

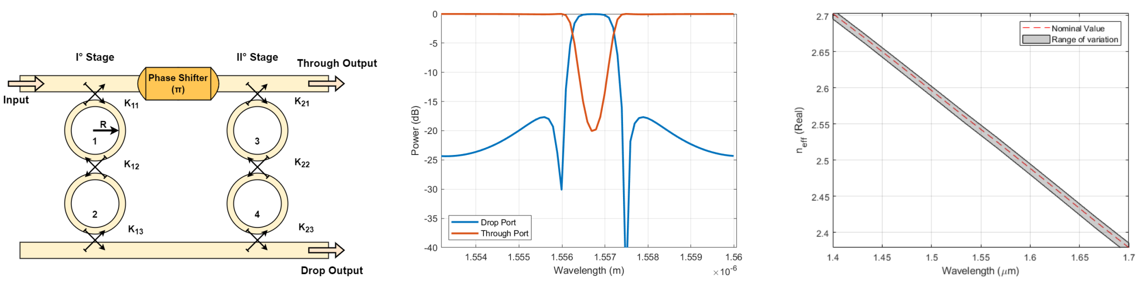
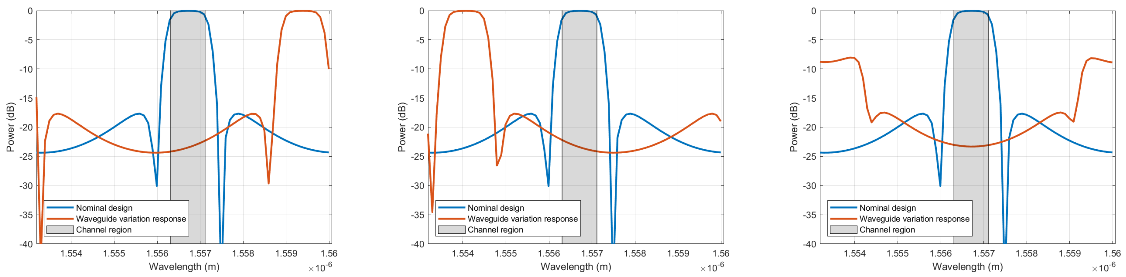


Fig. 1: (a) Circuit diagram for a two-stage ladder MRR filter; (b) nominal frequency response; (c) average effective index and range due to fabrication uncertainty.

In our vision, ML can offer a way to extract the information on the index variation directly from the transmission data, allowing precise and time-efficient tuning of the individual rings without requiring non-scalable iterative methods. The training of this ML agent has been done by extracting phase and power from 10^5 randomly perturbed configurations, applying a variation to the index of each ring within the range $\Delta n_{\text{eff}} = [-6 \times 10^{-3}, 6 \times 10^{-3}]$ (Fig. 1c), which has been obtained from the tolerance-aware simulation of the Silicon rib waveguide geometry [4] (width $W = 500\,\text{nm} \pm 0.5\,\text{nm}$ and height $H = 250\,\text{nm} \pm 2.5\,\text{nm}$).

The response of the filter is evaluated through an analytical model, which is used to compute both the effect of the index variation and the theoretical prediction based on the ML agent. The data extraction and prediction evaluation have been carried out considering a device with ring radius $R = 16\,\mu\text{m}$ and coupling parameters $k_{11} = k_{13} = 0.73$, $k_{12} = 0.1$, $k_{21} = k_{23} = 0.3$, $k_{22} = 0.2$. The tolerance on the coupling coefficients has not been considered at the current stage, as its effect is generally negligible with respect to the shift of the resonance peaks. In Fig. 2 the nominal response is compared to the three worst cases in terms of index shift: these represent the case with all four rings at the boundary of the index variation ((a), (b)) and the case with the maximum mismatch between the cascaded rings (c).



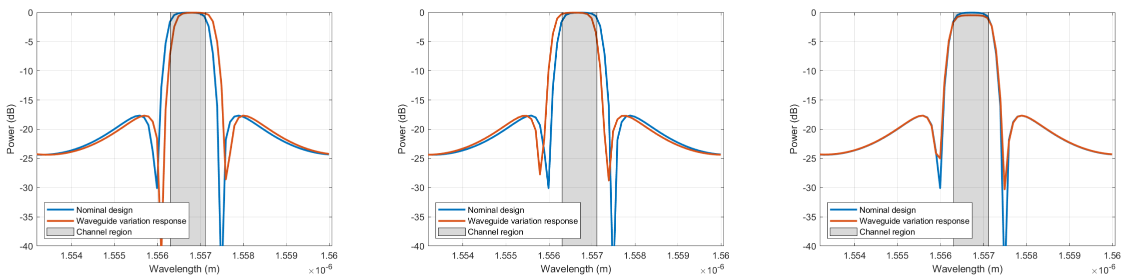
(a) $\Delta n_{\text{eff}} = (6\,,6\,,6\,,6) \times 10^{-3}$ (b) $\Delta n_{\text{eff}} = (-6\,,-6\,,-6\,,-6) \times 10^{-3}$ (c) $\Delta n_{\text{eff}} = (6\,,-6\,,-6\,,6) \times 10^{-3}$

Fig. 2: Frequency response comparison under the worst case assumption. The four variations of effective index refer to rings 1–4 as labeled in Fig. 1a, respectively.

3. Machine Learning Framework and Results

The proposed ML model is developed using the high-level Application Program Interface (API) of the TensorFlow© platform. The ML engine uses a Deep Neural Network (DNN) with three hidden layers and 10 neurons per layer. Mean square error served as the loss function and *ReLU* as the activation function in the simulated DNN model. The DNN model has been configured for 15000 training steps and a 0.001 learning rate. 70% of the dataset is used in training, and the remaining 30% is used in testing. Furthermore, the proposed DNN exploits the effective index shift as a label while using the frequency response in terms of phase and amplitude as a feature. As a metric for the ML prediction capability, we selected the range $\Delta n_{\text{eff}} = [-3 \times 10^{-4}, 3 \times 10^{-4}]$ as the acceptable error with respect to each ring, which yields the worst case responses depicted in Fig. 3. Based on our test set results, the agent predicts the indexes shift with acceptable accuracy in $\approx 90\%$ of the cases, with average error $\mu \approx 10^{-7}$ and standard deviation $\sigma \approx 8 \times 10^{-5}$.

Overall the ML has shown a strong and accurate prediction capability based on the data extracted from the model, largely removing the necessity for iterative tuning. In addition, the suggested technique can easily be adapted to a larger number of rings in more complex architectures.



(a) $\Delta n_{\text{eff}} = (3\,,3\,,3\,,3) \cdot 10^{-4}$ (b) $\Delta n_{\text{eff}} = (-3\,,-3\,,-3\,,-3) \cdot 10^{-4}$ (c) $\Delta n_{\text{eff}} = (3\,,-3\,,-3\,,3) \cdot 10^{-4}$

Fig. 3: Frequency response comparison for the target ML accuracy.

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