

Dimensional Metrology for Microcombs with Neural Networks

Ergun Simsek,^{1,*} Shao-Chien Ou,^{2,3} Gregory Moille,^{2,3} and Kartik Srinivasan^{2,3}

¹Department of Computer Science and Electrical Engineering, University of Maryland, Baltimore County, Baltimore, MD 21250, USA

²Joint Quantum Institute, NIST/University of Maryland, College Park, MD 20742, USA

³National Institute of Standards and Technology, Gaithersburg, MD 20899, USA

*simsek@umbc.edu

Abstract: Precise control of geometry and material properties is crucial for repeatable microcombs. We demonstrate that neural networks can predict microring dimensions from dispersion data with nanometer-scale accuracy, enabling fast, non-destructive characterization for establishing process control.

Optical frequency comb generation using integrated ring resonators (microcombs) has emerged as a promising technology for numerous applications in telecommunications, metrology, and quantum information science due to their compact footprint, low power consumption, and potential for large-scale integration [1]. Silicon nitride (Si_3N_4) microring resonators are particularly attractive due to low loss, high Kerr nonlinearity, and CMOS compatibility [2]. The resonator integrated dispersion (D_{int}), which describes its resonance frequencies in comparison to an equally spaced grid, helps determine the accessible frequency comb states and their spectral envelopes. Precise control of D_{int} is thus essential, as small deviations in its constituent components – the resonator geometry and material refractive indices – modify the location of important spectral features such as dispersive waves and impact how well microcombs can be tailored for application-specific purposes. Rapid assessment of fabricated device fidelity with respect to geometric and material property targets is essential, particularly with microcomb foundry fabrication now being realized at the 300 mm wafer-scale [3]. Typical approaches that combine ellipsometry and cross-sectional electron microscopy are time-consuming and destructive, limiting their utility. While D_{int} can be experimentally measured through calibrated swept-wavelength spectroscopy, the spectral extent and density of measurements required to accurately extract and separate geometry and materials properties from it is unclear. Here, we present three neural networks aimed at addressing these questions (Fig. 1): (i) to predict ring dimensions from D_{int} ; (ii) to classify the Sellmeier models associated with different precursor gas ratios from the D_{int} dataset; and (iii) to predict the D_{int} directly from ring dimensions.

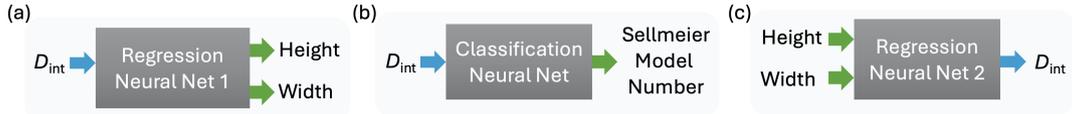


Fig. 1. Schematic diagrams of the three neural network architectures used in this study: (a) a fully connected network (20 layers, 64 neurons each, \tanh activation functions) for predicting the ring width and height from D_{int} . (b) Classification model with four hidden layers (128, 64, 32, and 16 neurons, leaky ReLU activation functions) and softmax output function for identifying the Sellmeier model from D_{int} . (c) A fully connected network with three hidden layers and leaky-ReLU activation functions for predicting the D_{int} from the ring widths and heights.

We consider fully SiO_2 clad Si_3N_4 microring resonators with a fixed outer radius of 23 μm , ring widths between 750 nm to 950 nm and heights between 620 nm to 720 nm. Effective indices are computed [4, 5] at 171 wavelengths (750 nm to 1600 nm), using four Sellmeier-type models for Si_3N_4 [6] representing different gas ratios ($\text{NH}_3:\text{SiH}_2\text{Cl}_2$) applied during the fabrication. D_{int} curves (see Fig. 2 (a) as an example) are extracted from the calculated effective indices [5, 7] with $\lambda=1060$ nm as the nominal pump wavelength; the overall parameter space is representative of recent foundry-fabricated microcombs reaching alkali atom wavelengths [3].

By employing the regression model displayed in Fig. 1(a), we show that the width and height of microring resonators can be predicted from the D_{int} dataset with remarkable precision, often with < 1 nm errors under noiseless conditions and within a few nanometers even in the presence of realistic measurement noise (e.g., ± 50 MHz uncertainty in determining resonance frequencies) as shown in Fig. 2 (b). Systematic evaluations across multiple Sellmeier models and varying noise levels reveal that the network maintains high fidelity, with R^2 values consistently above 0.95, confirming that such predictions remain reliable under experimental uncertainties. The accuracy depends strongly on the number and location of sampled dispersion values. For octave-spanning systems, while

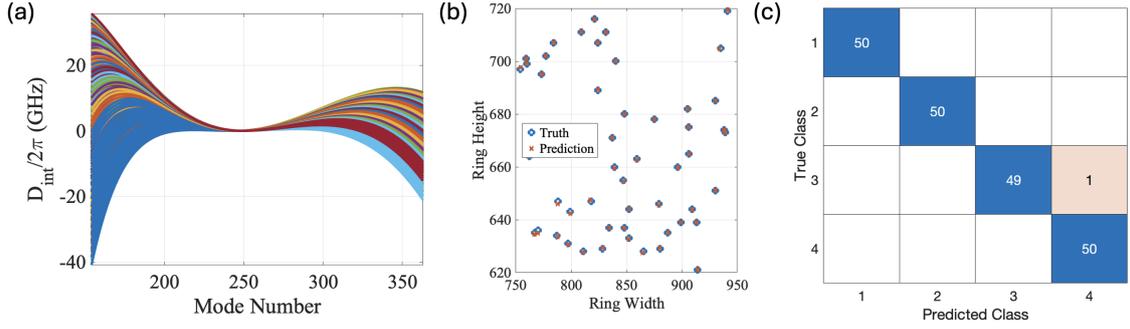


Fig. 2. (a) Simulated integrated dispersion ($D_{\text{int}}/2\pi$) versus mode number for a wide range of microring geometries, showing the variation in dispersion profiles. (b) Comparison between true (actual) microring dimensions (width, height) and those predicted by our neural network model, demonstrating excellent agreement. (c) Confusion matrix for classification under all noise conditions, showing robust identification of device classes with near-perfect accuracy.

as few as 20–30 strategically chosen samples are sufficient to provide robust estimates, broader spectral sampling away from the pump frequency improves accuracy substantially, reducing errors to the <10 nm regime.

Complementing this regression task, a classification model is trained to identify the Sellmeier dispersion relation of Si_3N_4 used in simulations. Unlike the geometry prediction problem, this classification proves to be highly robust to noise, achieving near-perfect accuracy even with added perturbations as shown in Fig. 2 (c). Importantly, 95% accurate classification is possible with as few as 21 dispersion samples, demonstrating that neural networks can distinguish between different refractive index models from partial spectral information.

The predictive power of these networks is further validated with experimental datasets, where the classifier correctly identifies the underlying Sellmeier model, and the regression network accurately predicts the fabricated resonator dimensions with errors consistently below 6 nm when compared with reference values [3]. Notably, including synthetic noise during training improves the model’s ability to generalize, yielding predictions that align more closely with the experiment [3].

A forward-prediction network, trained to reconstruct integrated dispersion spectra from ring dimensions by mapping geometry to polynomial coefficients, reproduces full dispersion profiles with high accuracy. Its predictions not only follow simulated data with near-perfect agreement but also match experimental spectra with impressive precision, demonstrating the neural network’s ability to bridge simulation and experiment seamlessly.

Our results highlight that neural networks provide a powerful and flexible framework for both inverse and forward problems in integrated photonics. They recover geometry with nanometer-scale accuracy from partial and noisy dispersion data, classify material dispersion models with near-unity fidelity, and reconstruct integrated dispersion spectra directly from ring dimensions. The demonstrated robustness against noise, combined with accurate performance on experimental datasets and even cases slightly beyond the training range, confirms their practical value for rapid characterization, inverse design, and dispersion engineering of integrated photonic resonators. By combining regression, classification, and forward prediction, our method provides a fast, non-destructive approach for wafer-scale monitoring and process control in photonic foundries.

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