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White Paper: AI-Enabled Integrated Nanophotonics at the NRC: Design, Fabrication, and Optical Metrology

Non-sensitive

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I. Introduction

Integrated photonics is a key technology platform for modern optical systems, enabling the integration of complex optical functionality onto compact, scalable chips. Over the past decades, advances in materials, fabrication, and design have transformed photonic integrated circuits from laboratory demonstrations into practical solutions for communications, sensing, computing, and quantum technologies. The field is now entering a new phase, where increasing device complexity calls for fundamentally new approaches to design, fabrication, and characterization.

This growing complexity places strong demands on integration density, driven by the need to reduce cost and energy consumption by packing more functionality into smaller footprints. Machine learning and artificial intelligence are rapidly expanding the scope of what is possible in integrated photonics. These approaches enable the discovery of new functionalities and unconventional structures that would be difficult to identify through traditional intuition-driven methods. By exploring high-dimensional design spaces, AI opens pathways to compact, multifunctional devices and reveals new physical regimes that can be harnessed for advanced photonic systems.

At the same time, these opportunities introduce new challenges. Exploring large design spaces can require extensive simulations and become computationally intensive. The optimization process may converge to different solutions while offering limited insight into performance limits or design trade-offs. The resulting designs can also be complex, sometimes relying on fine features that are difficult to fabricate reliably. As a result, small variations in manufacturing can lead to noticeable changes in performance. In this context, AI also plays a critical role in addressing these challenges.

To address these challenges, the NRC team, together with collaborators, has developed a suite of AI-enabled tools spanning design, fabrication, and characterization. Machine learning–assisted optimization guides the design process toward solutions that are not only high-performing but also robust and manufacturable. In parallel, adaptive layout correction compensates for fabrication inaccuracies, while data-driven optical metrology provides feedback to better understand device behavior and extract fabrication insights. Together, these capabilities support a more integrated and scalable approach to photonic development through continuous feedback across the workflow.

This document presents recent advances by the NRC team and collaborators in AI-enabled photonics, organized around three interconnected pillars: design, fabrication, and metrology. These efforts have been supported by the NRC AI for Design (AI4D) Challenge Program and the High Throughput and Secure Networks (HTSN) Challenge Program. Together, these developments illustrate how machine learning can accelerate device optimization, improve robustness to fabrication variability, and enable more reliable translation from concept to practical implementation (Fig. 1). Although the work presented here focuses primarily on silicon photonics, a leading platform for integrated photonics [1], the underlying methodologies are platform-agnostic. They provide a foundation that can be extended to a broader range of material systems, including III–V compound semiconductors and heterogeneous integration platforms, supporting future photonic technologies across diverse applications [2].

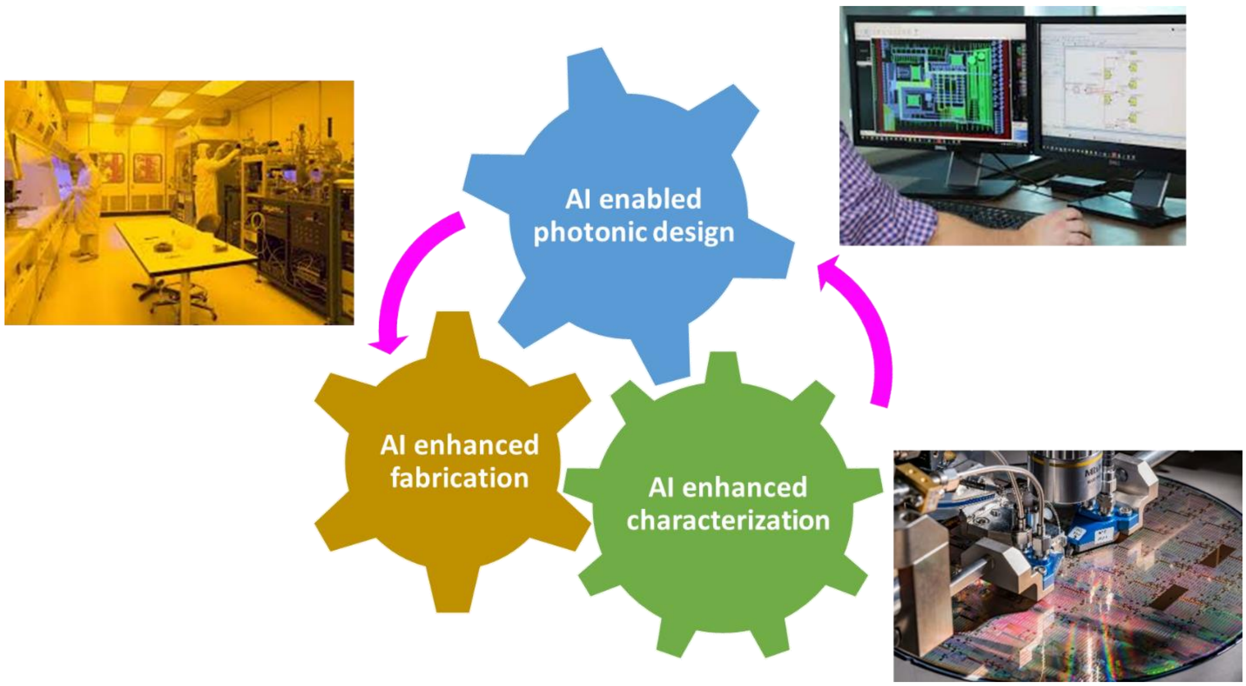

Fig. 1 AI enables a closed-loop workflow linking design, fabrication, and metrology in integrated photonics. Machine learning connects these stages through continuous feedback, enabling more efficient optimization, improved fabrication fidelity, and data-driven characterization.

II. Inverse Design of Photonic Devices

Conventional design methodologies are increasingly constrained by the growing complexity of photonic devices. These approaches typically rely on physical intuition and a library of standard building blocks, which can limit the exploration of more complex or unconventional solutions. Inverse design (Fig. 2) addresses this limitation by offering a fundamentally different paradigm: instead of starting from known structures, it begins with the desired optical functionality and determines a geometry that can realize it [3, 4].

This paradigm unlocks a much broader design space, enabling compact and unconventional solutions that would be difficult to conceive through intuition alone. In this sense, inverse design transforms the problem from form-to-function into function-to-form, where target optical responses, such as transmission spectra or modal properties, are translated directly into device geometries through algorithmic optimization.

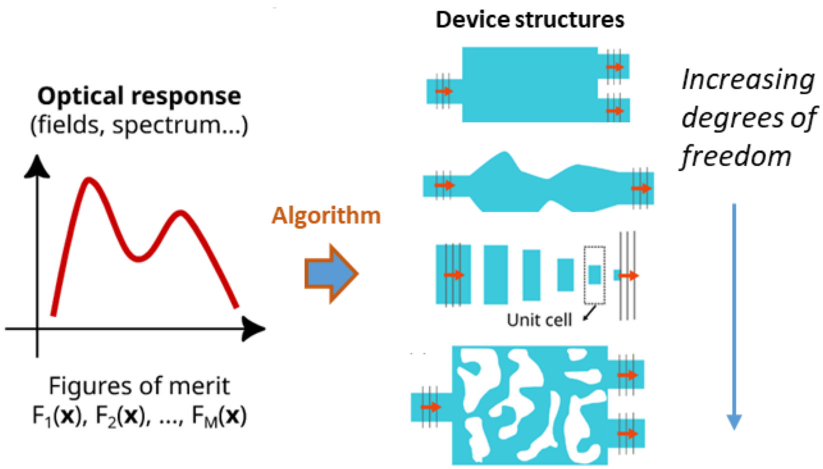

Fig. 2 From function to form: inverse design generates photonic structures from target performance. Desired optical responses are translated into device geometries through algorithmic optimization, enabling compact and non-intuitive designs.

Building on this framework, recent work has demonstrated how inverse design can be applied to a wide range of photonic components. One class of examples focuses on modifying device boundaries (Fig. 3 left panel), as demonstrated in broadband mode conversion and multiplexing [5]. By allowing geometries to evolve beyond conventional structures, efficient mode converters with footprints of only a few microns can be realized while maintaining low loss and low crosstalk over a wide wavelength range. These results highlight how even a relatively small number of parameters, when guided by algorithmic optimization, can unlock significant performance gains.

Inverse design can also be combined with physics-informed starting points. For example (Fig. 3 center panel), an ultra-compact mode size converter can draw on the Fresnel lens concept, originally developed for lighthouses to efficiently focus and direct light, and be further optimized to reduce aberrations, achieving high-quality mode transformation within a device length an order of magnitude shorter than that of conventional designs [6].

More generally, topology-based approaches extend this concept by exploring a much larger design space, where the material distribution itself is optimized in a free-form fashion (Fig. 3 right panel). This enables ultra-compact devices such as wavelength demultiplexers and power splitters with performance comparable to conventional designs, but at a fraction of the footprint [7-10].

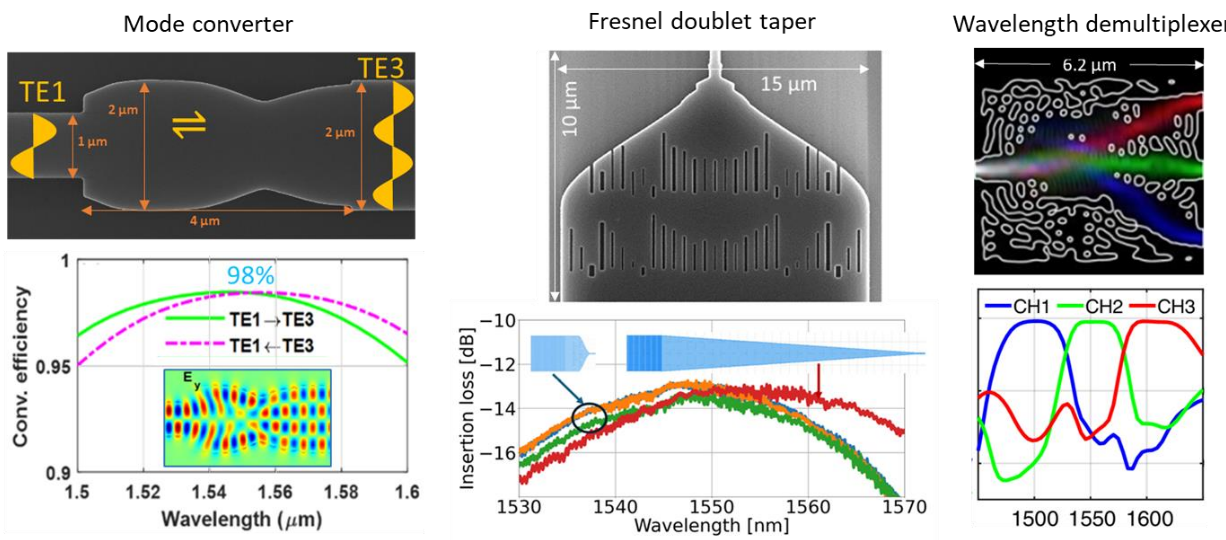

Fig. 3 Inverse-designed photonic devices enable compact, high-performance functionality beyond conventional design approaches. Examples include broadband mode converters [5], Fresnel-inspired tapers wavelength filters [6], and wavelength demultiplexers [7], achieving reduced footprint while maintaining efficiency and bandwidth.

Inverse design has also been extended beyond passive functionality. By incorporating temperature-dependent material behavior into the optimization, compact devices with built-in tunability can be realized. In this approach, a single structure can perform different functions under different operating conditions, such as switching or power splitting, within a footprint significantly smaller than conventional implementations [11].

Despite these advantages, inverse design introduces new challenges. Exploring large design spaces can require many simulations and become computationally intensive. The process may converge to different solutions while providing limited insight into performance limits or the structure of the design space. These challenges motivate the complementary techniques described in the following subsections, where machine learning is used to extract insight and accelerate design exploration.

II A. Design Space Mapping through Dimensionality Reduction

While inverse design is effective at identifying high-performing solutions, it provides limited insight into how many such solutions exist or how they relate to one another. As a result, the process can require many simulations, converge to different outcomes, and still leave open the question of what is ultimately achievable.

In practice, inverse design produces a sparse set of successful designs scattered across a high-dimensional space. Although each solution meets the specified performance target, their structure and relationships are not immediately visible. In many applications, additional performance considerations are also important but are not easily included in the optimization objective. Dimensionality reduction techniques transform this complex space into a lower-dimensional representation that captures the key features governing device performance [12, 13].

In this reduced space, high-performing designs form continuous regions rather than isolated points (Fig. 4). This enables systematic mapping of performance across multiple objectives, revealing trade-offs and identifying regions that are both high-performing and robust to variations. Dimensionality reduction therefore transforms inverse design from a search process into a structured exploration. Optimization generates candidate designs, while machine learning organizes, interprets, and connect them, allowing designers to navigate the design space more efficiently and understand what is ultimately achievable. While the mechanics of dimensionality reduction and structured exploration may differ, this approach is applicable to both intuitions driven parameterized structures as well as free form designs.

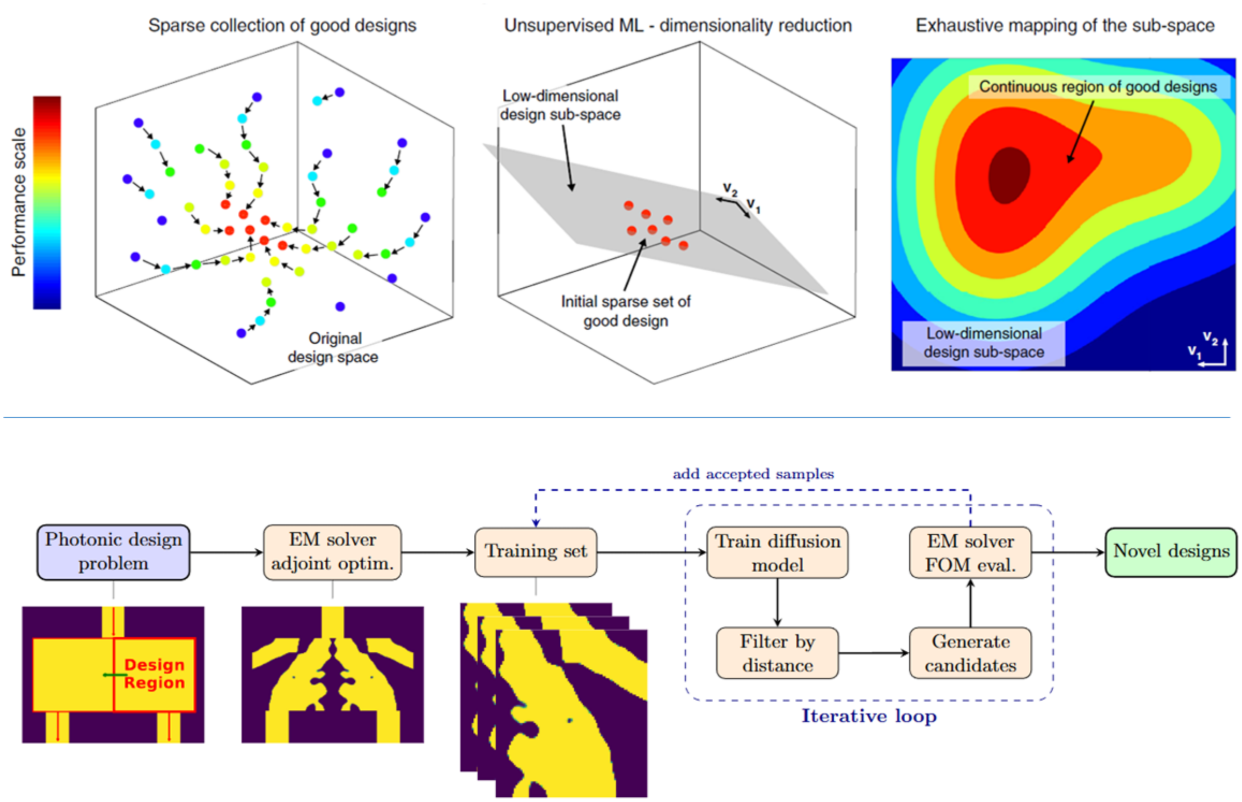

Fig. 4 Dimensionality reduction reveals structure within high-dimensional design spaces. Sparse optimized solutions can be mapped onto a lower-dimensional space, where continuous regions of high performance and robustness become visible, enabling systematic exploration and trade-off analysis. Top: the workflow for parameterized designs; Bottom: the workflow for free-form designs.

II B. Pseudo-3D Surrogate Modeling for Efficient Design Exploration

A key limitation of inverse design is the large number of simulations required to explore complex design spaces. This challenge is compounded when device performance depends on fine structural features, which often require full three-dimensional simulations. As a result, the design process can become computationally intensive and time-consuming.

Machine learning can address this by developing surrogate models that approximate physical behavior at a much lower computational cost. In grating coupler design, the introduction of metamaterial unit cells has significantly expanded design flexibility, enabling enhanced control over the effective index and radiation properties. This has led to successful demonstrations of high-performance devices, including improved directionality and coupling efficiency [14]. However, as the unit cell becomes more complex to address specific challenges, such as achieving perfectly vertical emission while suppressing back-reflection, the optical response increasingly depends on subwavelength features and their interaction with the surrounding environment, making simplified models insufficient. Conventional effective-medium approximations, which typically assume an infinitely extended periodic segmented region, become less accurate in capturing environment-dependent interactions in finite and non-uniform structures.

To overcome this limitation, we developed the MetaStripNet approach that provides a pseudo-3D surrogate model that learns the relationship between the metamaterial effective refractive index and complex device geometries, while explicitly accounting for the local environment (Fig. 5). This enables the model to capture key three-dimensional effects without requiring repeated full 3D simulations. By extending effective-medium concepts with a data-driven framework, it enables fast and accurate prediction of device performance.

This acceleration makes it practical to explore multi-objective design problems, which typically require a large number of optical simulations. Such approaches are useful when several metrics, such as efficiency, reflection, and fabrication constraints, must be balanced. Instead of producing a single optimal design, the method reveals a set of viable solutions forming a Pareto front, allowing designers to visualize trade-offs and identify robust regions in the design space [15, 16].

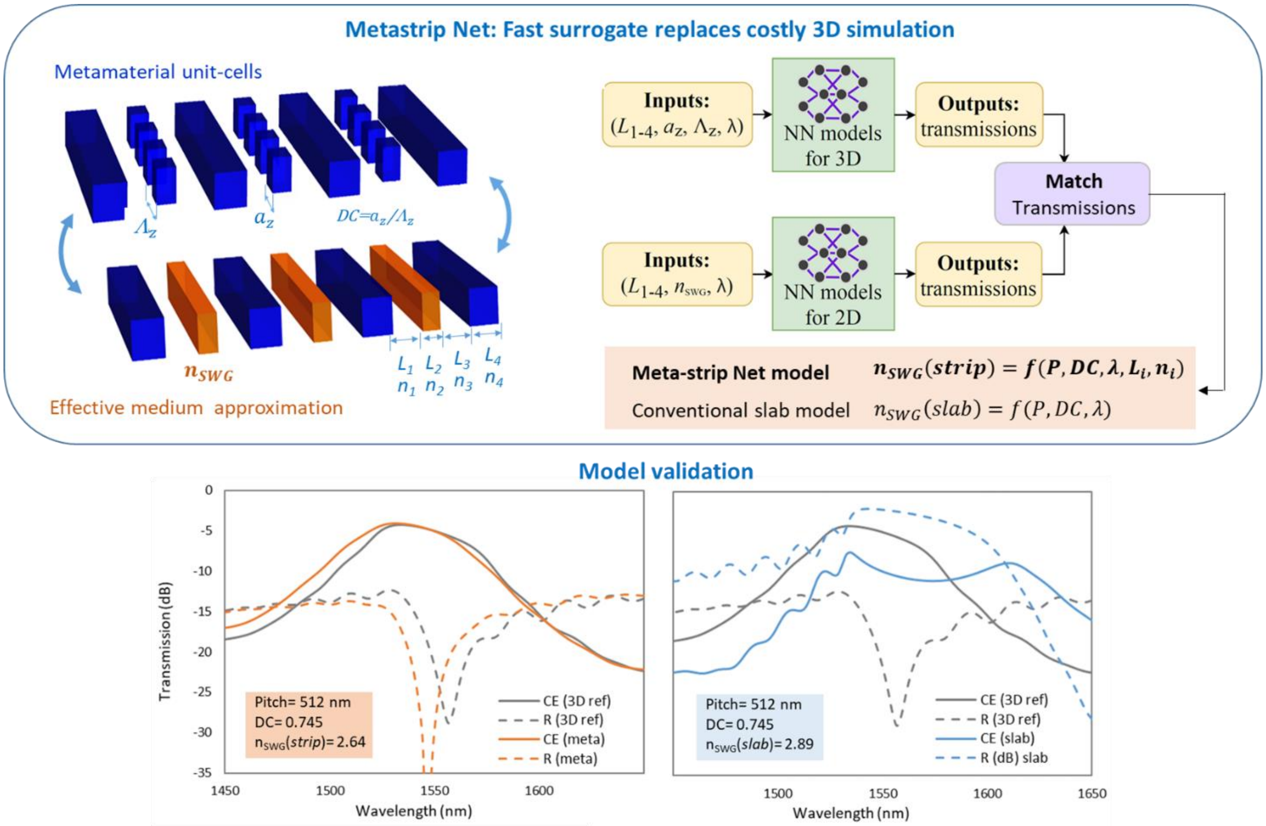

Fig. 5 Environment-aware Pseudo-3D surrogate modeling replaces costly full-wave simulations. By learning geometry- and environment-dependent effective indices, the MetaStripNet approach captures essential three-dimensional effects at a fraction of the computational cost, enabling rapid multi-objective optimization.

III. AI-Driven Layout Correction and Digital Fabrication Twin

While inverse design enables high-performance devices in simulation, fabricated structures often exhibit degraded performance due to process imperfections at the nanometer scale. These deviations can vary across a device and are difficult to capture using simple rule-based corrections, particularly for irregular geometries.

To address this, the NRC team and collaborators have developed a machine-learning-based pipeline to predict and compensate for geometric distortions introduced during fabrication processes, such as lithography and etching [2, 17-20]. Fabrication processes deform fine features, including corner rounding, bridges narrowing, and merging closely of spaced elements, thereby shifting the optical response away from the intended design (Fig. 6). Such deviations include both systematic changes and stochastic variations. A neural network architecture suitable for image analysis tasks, trained on paired datasets of designed layouts and corresponding SEM images of fabricated structures, predicts these distortions [17]. Such a model is useful for assessing the impact of geometric distortions on the optical performance of the device. More recent developments include generative-model-based approaches that capture finer structural details and naturally represent fabrication variability present in manufacturing processes [21]. These tools enable virtual design validation, reducing the need for costly test fabrication runs.

A similar methodology is further leveraged to develop adaptive design corrections that compensate for anticipated fabrication deviations. Adaptive layout correction modifies the design locally, taking into account the surrounding geometry rather than applying uniform biasing, and captures proximity-dependent effects when predicting distortions [18]. This significantly improves agreement between simulated and measured device responses, recovering spectral alignment and overall performance [19]. By tightening the correspondence between design and fabrication, this approach reduces the number of costly fabrication iterations and enables a more robust design workflow, improving yield and supporting reliable deployment of complex photonic systems.

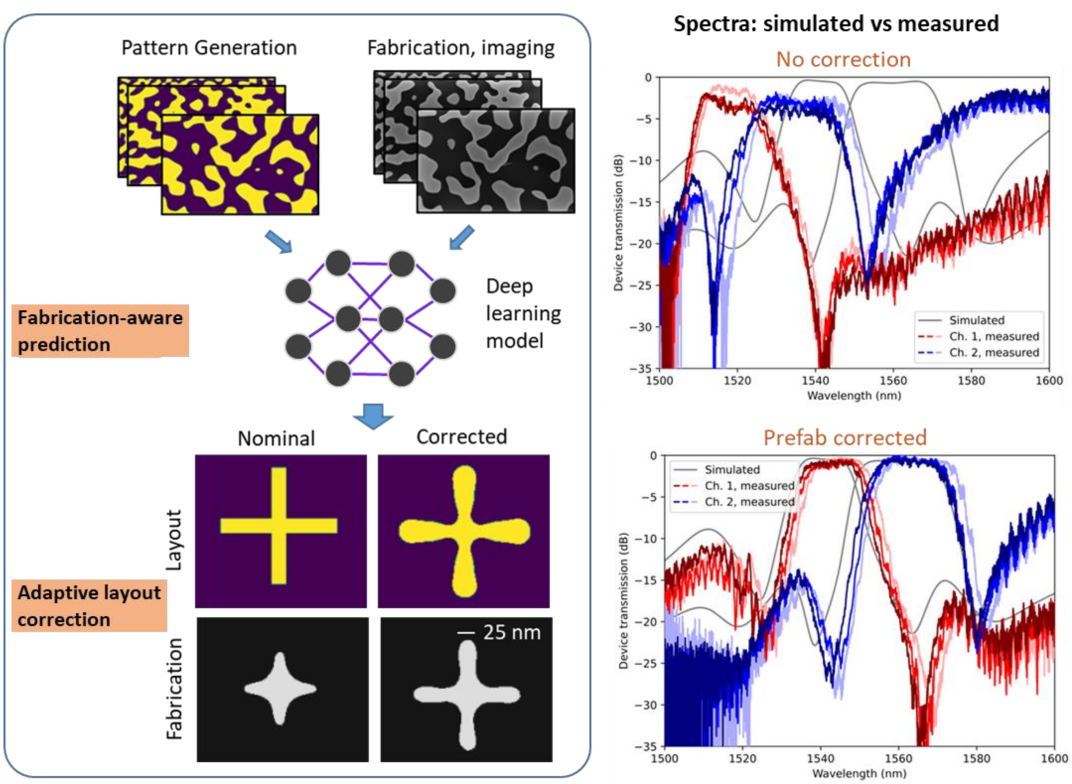

Fig. 6 Machine-learning-based layout correction compensates for fabrication-induced distortions. Adaptive pre-distortion of device layouts significantly improves agreement between simulated and measured responses, recovering spectral performance and reducing iteration cycles.

IV. AI-Enabled Optical Metrology and Fabrication Intelligence

As photonic devices become more complex and compact, accurate and efficient characterization becomes increasingly important. Optical metrology provides one of the most precise and scalable approaches, as device spectra are inherently sensitive to nanoscale geometry. Unlike imaging-based techniques such as scanning electron microscopy, optical metrology is non-destructive, fast, and therefore well suited for wafer-scale deployment. Monitoring structures can be embedded across a wafer, enabling spatial mapping of process variations with high throughput. Conventional methods based on ring resonators or Mach-Zehnder interferometers extract parameters tied to waveguide dimensions of approximately 500 nm, providing high sensitivity to dimensional variations at that scale but limiting their applicability to a narrower range of feature sizes. They also rely on semi-analytical models, which restrict the retrievable parameters primarily to simple waveguide cross-sections, such as width and height.

To overcome these limitations, grating structures with complex unit cells are used as a dedicated platform for optical metrology (Fig. 7). These devices are intentionally designed to be highly sensitive to dimensional changes, with their radiative response encoding rich structural information associated with subwavelength features across a wide range of length scales. Variations in geometry translate directly into measurable changes in the optical spectrum [22]. Machine learning models can then interpret these spectral signatures to retrieve multi-dimensional, subwavelength structural parameters without requiring direct imaging. This enables high-precision, non-destructive characterization across a wide range of feature sizes within a single measurement.

This capability enables a form of fabrication intelligence, where optical measurements are translated into actionable information about device geometry and process variations. When deployed at the wafer scale, it provides rapid feedback, improves process control, and accelerates convergence between design and fabrication.

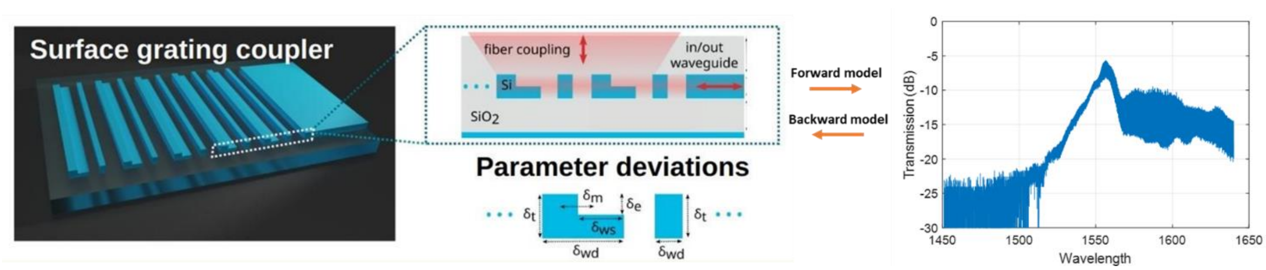

Fig. 7 Optical spectra encode rich structural information, supporting non-destructive metrology. Gratings with complex unit cells are selected for their strong sensitivity to geometry across a wide range of feature sizes, enabling machine-learning-based retrieval of multi-dimensional, subwavelength parameters beyond conventional waveguide-based methods.

V. Conclusion

This document describes a suite of AI-enabled methods to address ongoing challenges in advanced silicon photonics. It represents an integrated approach to nanophotonic device engineering, where inverse design, fabrication-aware correction, and optical metrology are linked through machine learning into a coherent workflow. While each stage is addressed using methods tailored to its specific requirements, these elements work together in synergy, enabling both the discovery and practical realization of increasingly complex on-chip functionalities. Rather than treating design, fabrication, and characterization as separate steps, this framework establishes a continuous, data-driven process in which each stage informs and improves the others.

Within this paradigm, machine learning supports inverse design of compact, high-performance devices, organizes high-dimensional design spaces through dimensionality reduction, and accelerates design exploration using pseudo-3D surrogate models such as MetaStripNet, thereby reducing computational cost. It also enables prediction and compensation of fabrication-induced distortions through data-driven layout adjustment, and retrieval of multi-dimensional structural parameters from optical spectra using grating-based metrology. Together, these capabilities extend both the accessible design space and the range of physical effects that can be efficiently modeled and controlled.

As device complexity continues to increase, this approach becomes increasingly important. It enables systematic exploration of complex design spaces, improves tolerance to fabrication variability, and provides more direct visibility into the relationship between device geometry and performance. By combining compact inverse-designed structures, fabrication-aware correction, and non-destructive optical metrology, the framework supports the realization of devices that are not only high-performing in simulation but also reliable in practice. More broadly, it narrows the gap between design intent and fabricated outcome, enabling more predictable and scalable photonic system development.

Looking forward, the combination of physics-based modeling and machine learning is expected to play a central role in the evolution of integrated nanophotonics. Although demonstrated primarily in silicon photonics, these methods are broadly applicable and can be extended to other material platforms and heterogeneous integration schemes. By linking design, fabrication, and measurement within a unified but modular framework, AI-enabled photonics provides a pathway toward more adaptive, interpretable, and scalable photonic technologies across a wide range of applications.

Opportunity details

License available

Some related patents

Patent granted: D. Melati et al., ‘’Waveguide antenna device’’, US12449598B2, Oct. 10, 2025

Patents pending (with McGill co-inventors):

Y. Grinberg et al., ‘’ Deep learning based prediction and correction of fabrication-process-induced structural variations in nanophotonic devices’’ US 18/842,338 (filing date Feb 28, 2023); CAN 16258-142 (322519)

Y. Grinberg et al., ‘’Ultra-Compact Silicon Photonic Spatial Switch’’ US 18/965,018 (filing date December 2, 2024); CAN 3,258,134

Collaborations

The NRC team has been working with collaborators from McGill University, University of Ottawa, University of Montreal, and Center for Nanoscience & Nanotechnology (C2N) of CNRS (France).

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