Machine learning for design optimizations and prediction of optical chip performance

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ABSTRACT

Artificial intelligence (AI) and machine learning (ML) have tremendous potential for increasing the scale and reach of the photonics industry. We present how the use of AI/ML has revolutionized the field of photonic integrated circuit design and manufacturing, and resulted in mass deployments of high-performance optical chips for multiple classes of datacom and telecom applications. First, we discuss our use of a deep neural network multivariate regression model to optimize the individual design parameters of hundreds of optical chips on a given mask. This work successfully addresses the systematic processing variations within a wafer, resulting in an unprecedented homogeneity of performance of optical chips in a high-volume production environment. Second, we present our approach of using ML to predict the performance of optical devices by wafer probing. This novel approach eliminates the expensive and time-consuming process of optical chip testing and instead relies on a wafer probe measurement to infer the performance of hundreds of chips on a wafer. We discuss the complexity of the problem of predicting the performance in multi-dimensional parameter space, the inherent challenges that cannot be overcome by traditional methods, and the reasons why ML is an essential tool to solve this problem. The support vector machine (SVM) that we developed performs nonlinear binary classification based on a regression from the probe measurement, allowing unprecedented control over our process, including in-situ monitoring of wafer fabrication and real-time process adjustments, and thus achieving consistently high performance of optical chips at high production volumes.

Keywords: machine learning, artificial intelligence, deep learning, AI/ML, SVM, photonic integrated circuits, integrated optics, fabrication

1. INTRODUCTION

One of the biggest factors in the phenomenal growth in information exchange that occurred over the past three decades is the deployment of wide-scale optical communication systems. High-capacity optical fibers, combined with the use of integrated optical devices to control light, allow for optical networks with advanced routing and multiplexing capabilities. Today, optical technologies dominate long-distance and datacenter communication, and are beginning to increasingly penetrate short-reach links such as intra-chip or chip-to-chip communication.

Artificial intelligence (AI) and machine learning (ML) have recently emerged as a powerful new approach for solving previously intractable problems. The list of domains that have already benefitted from ML-based solutions is diverse, and includes epidemiology, natural language processing, fraud detection, e-learning and energy generation. Looking into the near future, the United Nations has predicted that some of the most pressing environmental, social and economic problems of our civilization will be among the biggest beneficiaries of AI and machine learning technologies.[1] These parallel advancements are not a coincidence – during the past decade, advances in hardware architectures have greatly accelerated machine learning computations, allowing it to expand from a narrow computer science research field to a pivotal research instrument in many areas. The common characteristic that allows machine learning to become so useful in seemingly unrelated fields is its tremendous capability to capture essential features from vast amounts of high-dimensional data.

Similar to other industries, the photonics industry has began adopting AI and ML techniques to further both research and deployment of optical technologies. Big advances have been made in using deep learning methods to deal with intractable high degrees-of-freedom structures in the field of inverse design.[2] Other successful applications include using machine learning to improve optical microscopy,[3] optical communication[4] and ultrafast optics.[5]

Within the photonics field, photonic integrated circuits have grown into a powerful and versatile platform that is able to meet the challenging demands of today's high-speed communication systems.[6,7] Photonic circuits possess high optical performance and are well suited for both monolithic and hybrid integration. However, achieving consistently

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reproducible performance has been a significant challenge in the photonics industry.[8] In any fabrication process, some variation of physical parameters within a wafer is inevitable. In photonics, even minute fabrication variability often results in performance degradation. Traditionally, the problem of performance inhomogeneity stemming from process variations has been handled by relying on 100% optical testing of devices, yet this very time-consuming process becomes prohibitively expensive in high volume applications. Offshoring labour-intensive production steps is often not a viable option due to labor practices in foreign jurisdictions and exposure to geopolitical risks.

In this paper, we present how the use of AI/ML has revolutionized the field of photonic integrated circuit design and manufacturing, allowing mass deployment of high-performance optical chips in datacom and telecom applications. We describe our use of deep learning to optimize the multi-dimensional design parameter space for hundreds of optical chips on a production mask. We also discuss our approach of using ML to predict the performance of optical devices by wafer probing, as an alternative to the time-consuming and often prohibitively expensive process of optical chip testing. These approaches allow us to achieve an unprecedented control over our fabrication process, including in-situ monitoring of wafer fabrication and real-time process adjustments, and thus achieving consistently high performance of optical chips at high production volumes.

2. DEEP LEARNING MODEL FOR DESIGN OPTIMIZATIONS

Photonic integrated circuit technology has been widely used to realize high-performance wavelength division multiplexing (WDM) devices for datacom and telecom applications.[9,10] A typical 6" production wafer contains hundreds of optical devices. An example of a production mask with about 600 four-channel multiplexer devices is shown in Figure 1, along with typical transmission spectra expected from each of the devices on a wafer.

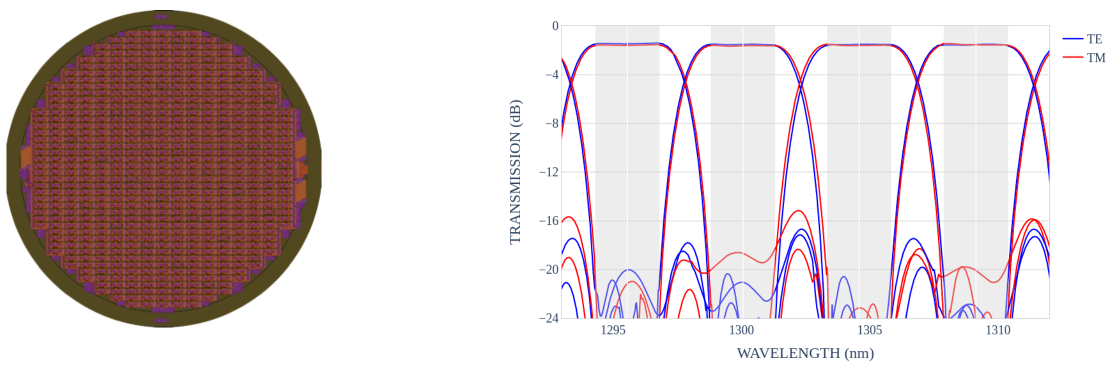

Figure 1. (a) A 6" production mask with four-channel multiplexer devices for LAN-WDM applications. (b) Typical spectra expected from each of the multiplexer devices, for TE and TM polarizer light.

Process uniformity and consistency is critical in the manufacturing of photonic chips.[8] This includes variations of physical parameters within a wafer, as well as the differences between batches of wafers – both pose a significant challenge in achieving reproducible performance in volume production. Traditionally, standard statistical methods are used to compensate for systematic process non-uniformities. This approach is based on deriving some physical or spectral characteristic of the devices, and then compensating for it in subsequent iterations of the mask. This traditional approach has two limitations – first, it requires the judgment of a human and thus is usually restricted to handling low-dimensional data, and second, it can compensate only for a limited set of already known dependencies, while not being able to capture dozens of chip-specific dependencies that may not have yet been discovered.

Machine learning offers an entirely new approach for addressing this problem thanks to its ability to handle high-dimensional data. We use a deep neural network to study the variations in the performance of individual chips, and then predict the adjustments required to compensate for such variability in the design of the production mask. This is a multivariate regression problem where the device spectrum is correlated to the device parameters. Figure 2(a) shows an example of the data used to train the model for the prediction of optimized design parameters for a four-channel multiplexer using a supervised learning strategy (Figure 2(b)). Each of the training instances $\mathbf{x}^{(i)}$ is a normalized spectrum generated through simulation, while the label $\mathbf{d}^{(i)}$ consists of 18 design parameters that are used to construct a multiplexer device. The training dataset consists of 900,000 simulated spectra, with 1/10 of it reserved for the validation set.

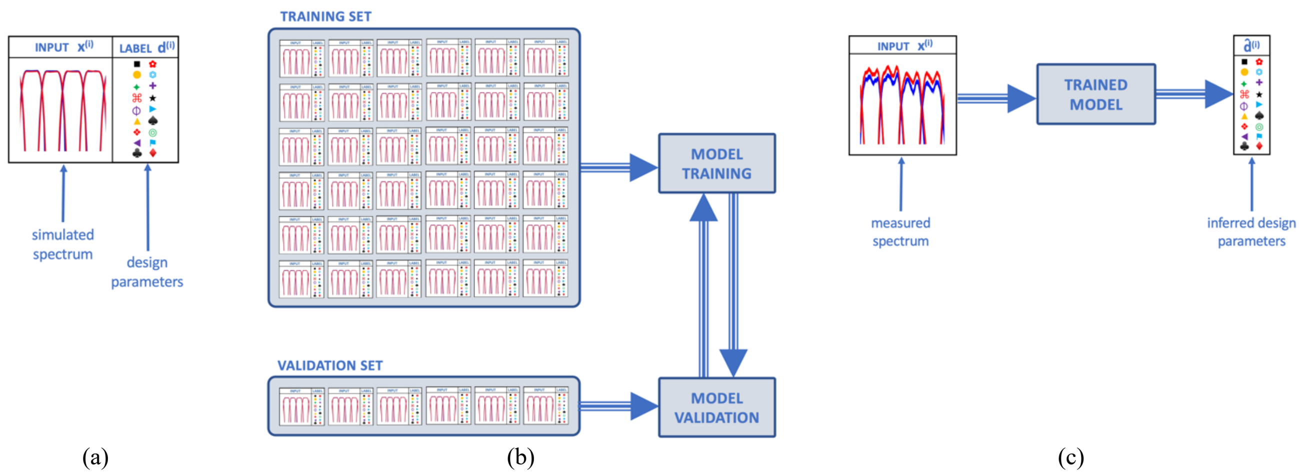

Figure 2. (a) Training instance $\mathbf{x}^{(i)}$ that consists of a normalized spectrum and a label $\mathbf{d}^{(i)}$ with 18 design parameters. (b) A supervised learning setup used to train the neural network. (c) Using the trained neural network to infer design parameters from a measured spectrum.

Once the model is trained, we can feed the measured spectra to the model, and use it to infer the vector of 18 design parameters $\hat{\mathbf{d}}^{(i)}$ that characterizes a particular multiplexer chip, as shown in Figure 2(c). $\hat{\mathbf{d}}^{(i)} - \mathbf{d}^{(i)}$ is therefore the difference between the actual (i.e. as-fabricated) design parameters and the intended design parameters. This difference is captured for each individual chip on a wafer. We can use this chip-specific difference to compensate for the systematic process variation in a new version of the mask with a goal of achieving a highly uniform performance.

To validate the approach, we applied the steps above to the production mask shown in Figure 1(a). The devices on the initial mask were designed to be identical, except for a refractive index distribution correction computed by traditional statistical means. Despite the built-in compensation for systematic refractive index variations, we observed that nominally identical devices can have large variations in their performance, as evidenced by the juxtaposition of the two spectra shown in Figures 3(a) and 3(b). Figure 3(c) overlays the spectra of the 20 worst-performing chips on the mask, providing further evidence that substantial inhomogeneity in the performance of the devices persists due to unknown process variations.

Using the training and inference process shown in Figure 2, we used the model predictions to insert corrections into each of the chips on the mask, thereby producing a ML-enhanced version of the production mask. Figure 3(d) overlays the spectra of the 20 chips that performed poorly in the initial version of the mask after deep learning was applied to optimize their design parameters. Comparison of these spectra to those in Figure 3(c) shows the success in transforming clearly underperforming devices to devices with excellent optical characteristics. This approach gives us the ability to optimize the multi-dimensional design parameter space and thus achieve performance homogeneity over hundreds of devices fabricated on a single wafer. The power of machine learning stands in stark contrast to our limited ability to reduce the variation in performance by traditional means.

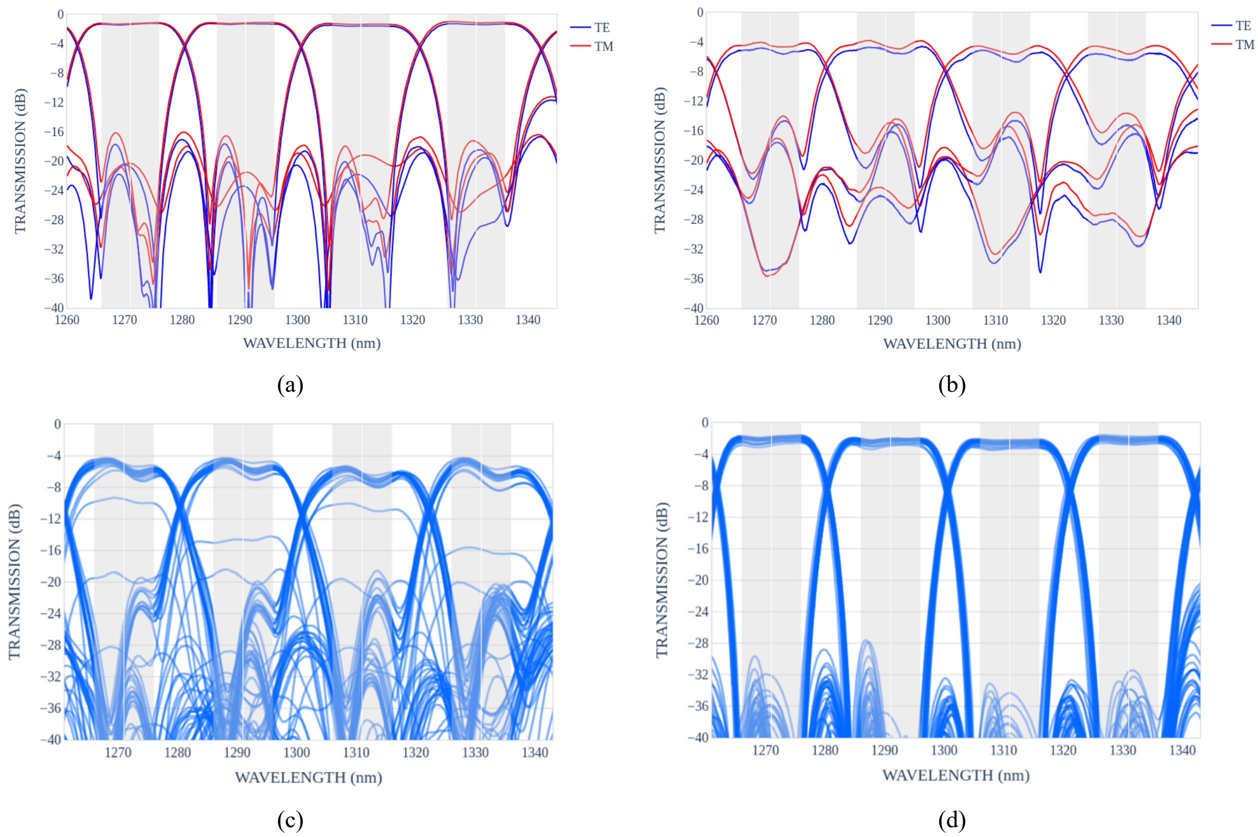

Figure 3. (a) A transmission spectrum for a high-performing chip. (b) A transmission spectrum for an identically designed chip from the same wafer, but one that exhibits poor performance due to process variabilities. (a) Overlaid transmission spectra for 20 worse-performing chips in a production mask with 582 devices. (b) Overlaid transmission spectra for the same 20 chips after deep learning was applied to optimize the design parameters and create a ML-enhanced version of the production mask.

3. SUPPORT VECTOR MACHINE FOR PREDICTION OF OPTICAL PERFORMANCE

Optical testing of chips is an extremely labour-intensive task that does not lend itself readily to high-volume production. It necessitates dicing a wafer into individual chips or bars to allow access to the chip I/Os, precise alignment of an optical fiber or fiber array to the inputs and outputs of the chip, followed by a tunable laser scan to obtain the transmission spectra over the required operational wavelength range at orthogonal polarizations. Even with experienced personnel and after investment in tooling, it takes several minutes to test a single four-channel chip; this easily scales to multiple working days to fully characterize a single production wafer.

We have developed a new technology that relies on a wafer probe and collects enough information to predict the performance of all the chips on the wafer, without requiring the wafer to be diced. The wafer probe collects metrology data at 64 locations around the wafer, as shown in Figure 4(a), obtaining the spectra shown in Figure 4(b). Note that the spectroscopic signature obtained from the probe measurement is extremely weak and has a non-systematic noise component. The goal is to use this signature to accurately predict the pass / fail state of all chips on the wafer, whose spectra looks distinctly different as evidenced by the comparison of Figures 1(b) and 4(b).

We have developed a support vector machine (SVM) that performs nonlinear binary classification (pass / fail) based on a probe measurement. The prediction of the model for a particular wafer is shown in Figure 4(c). For comparison, the actual performance of the same wafer, after it was diced and the transmission spectra of each chip was individually measured using the traditional optical test method, is shown in Figure 4(d). We use the receiver operating characteristic (ROC) curves, and specifically the area under the curve (ROC AUC), to cross-validate our binary classifiers, and employ an incrementally learning algorithm so that the accuracy of the prediction improves as more data becomes available.

In contrast to the multi-day effort that it takes to obtain the pass / fail map shown in Figure 4(d), the total time needed to mount, align and obtain the spectroscopic signatures using the wafer probe method is 12 minutes; once the spectrum is obtained, the inference of the map shown in Figure 4(c) is instantaneous. The power of this approach goes well beyond the economical aspect of chip testing – because the wafer remains intact and the probe measurement requires minimal effort, we are able to do in-situ monitoring of wafer fabrication and introduce real-time adjustments as required. This gives us an unprecedented control over the fabrication process, enabling consistently high performing wafers at large production volumes.

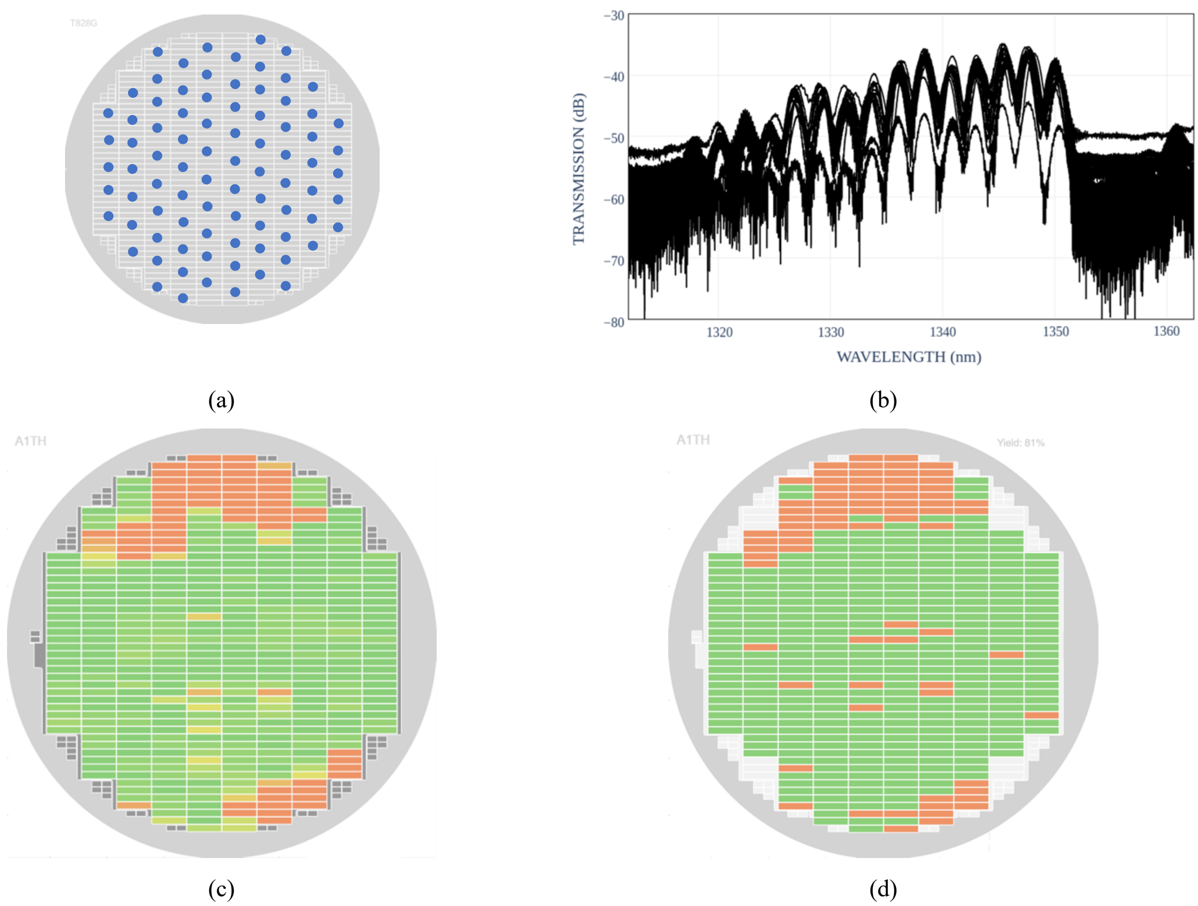

Figure 4. (a) A wafer probe obtains metrology data from 64 locations around the wafer. (b) Typical spectroscopic signature obtained from the wafer probe measurement. (a) SVM prediction of the wafer performance based on the probe measurement (green: predicted pass, orange: predicted fail, colors in between indicate the degree of confidence of the measurement). (b) Actual wafer performance after traditional optical chip testing (green: pass, orange: fail).

4. CONCLUSIONS

Machine learning has the capacity to capture features from vast amounts of high-dimensional data. In this paper, we described how AI/ML was used in the field of photonic integrated circuit design and manufacturing. We used deep neural network multivariate regression model to optimize the individual design parameters of hundreds of devices on a mask, resulting in a ML-enhanced production mask that achieves unprecedented uniformity of performance in high volumes. We also used a support vector machine (SVM) to predict the performance of optical chips in multi-dimensional space, a complex problem that could not be addressed by traditional means and necessitated the use of machine learning techniques. The proposed solution not only renders obsolete the labour-intensive process of optical chip testing, but also transforms the optical chip fabrication process, allowing in-situ monitoring of wafers and real-time process adjustments. The combination of these two approaches brings the power of machine learning to both the design of optical chips and their manufacturing, demonstrating the tremendous potential of AI/ML for increasing the scale and reach of the photonics industry.

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