# Advancing test and characterization methods for photonic integrated circuits with (automation and) machine learning

R. Jansen[1,2], D. Pustakhod[1,2], and S. Latkowski[1,2]

[1] Eindhoven University of Technology, 5612 AP, Eindhoven, The Netherlands
[2] PITC (Photonic Integration Technology Center), 5656 AE, Eindhoven, The Netherlands

*This paper presents a comprehensive overview of the progress made in scaling up testing and characterization methods for Photonic Integrated Circuits (PICs). The focal point of this work lies in the development and improvement of a generic (semi-)automated measurement setup, currently capable of running more than 300 optical measurements (including optical alignment) per day. A crucial aspect of this work has been the establishment of a robust data analysis framework, enabling rapid processing and visualization of extensive data sets that are generated during automated tests. Furthermore, the measured spot size data was used together with a DBSCAN algorithm to develop a classification scheme capable of qualifying the optical alignment quality.*

## Introduction

As the demand for Photonic Integrated Circuits (PICs) continues to surge in domains ranging from telecommunications[1] to (bio)sensing[2], so does the need for faster, scalable and reliable test and characterization methods on all levels of the production chain [3]. Achieving known-good-die identification and optimizing overall yield relies heavily on datasets with statistical significance. However, the complexity of electronic-photonic test processes can be time-consuming, making them dominant contributors to the production costs of integrated photonics [4]. Addressing this challenge, there is a pressing requirement for rapid and modular test solutions, introducing not only automation for shorter test times but also quick data analysis for immediate insights into production yield and test setup performance. The current lengthy testing processes necessitate a shift towards automation and machine learning (ML) techniques to expedite testing and unlock a myriad of potential applications [5].
This work focuses on the development of an automated test setup together with a classification algorithm derived from measurement setup data. The algorithm aims to provide a comprehensive quality assessment of measurements, with a particular emphasis on optical alignment properties.

## Generic automated setup

**Capabilities** The generic automated setup is running a procedure which is based on a modular test software framework described in [3]. It uses open standards in the form of standard file formats for chip, equipment and measurement definition as well as open file formats for storing and exchanging data. This gives any user the capability to run a variety of automated measurements on both passive and active devices with a large library of measurement equipment. The setup takes care of the coarse and fine optical alignment of two polarization maintaining lensed fibers by a combination of mechanical and piezo stages. Additionally the setup can be equipped with an electrical probecard

or individual probe needles in order to supply/measure voltages and/or currents. The present capabilities of the setup encompass conducting over 300 optical measurements per day, including alignment with more than 10 nm precision and repeatability exhibiting a maximal power variation of 0.012 dB[3]. This gives access to a large amount of data which can be analyzed.

**Operation** The flow of the test procedure is shown in figure 1. An observation is defined as a measurement on an input/output (I/O) combination including optical alignment. On each observation, the fibers are initially moved to a target position based on the description files of the chip and measurement (coarse positioning in fig. 1).

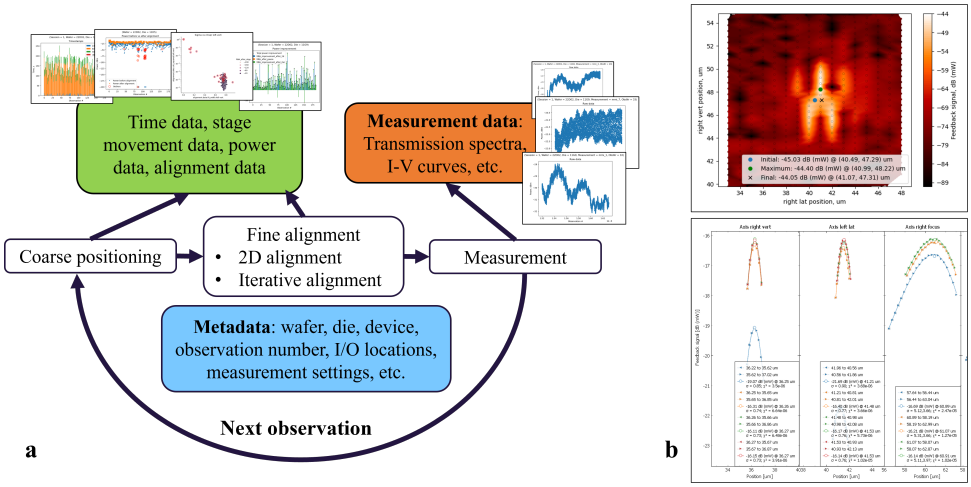


Figure 1: a—Flow diagram of the generic measurement setup operation. b—Example plots of fine alignment sub-steps data.

Then, fine fiber alignment is performed which consists of at most two sub-steps. If the optical power is below a certain threshold after this coarse alignment, no first light was found, a 2D mapping algorithm is triggered. This measures the power in a two-dimensional snake pattern in the lateral and vertical directions. The second algorithm, which is always used, performs an iterative hill-climbing for each axis in 3D space until a predefined power spread or the maximum number of iterations is reached. After optical alignment the measurement is performed and the procedure is repeated for the next observation.

**Collected data** The collected data comprises metadata containing information regarding the measurement, such as the wafer and die names, I/O locations, and measurement procedure settings. In the alignment process, timestamps, power data, stage movement data and alignment properties are recorded at various stages during each observation. These alignment properties, extracted from the fitting process of the expected coupling profiles of Gaussian beams, involve analyzing the width of the peaks $\sigma$ and the goodness of fit $\chi^2$.

## Building a classification model

The primary objective of the classification is to gain insight into the quality of the optical alignment for each observation. Specifically, we are interested in whether the optical fibers were aligned to the fundamental mode of the waveguide. The outcome of the assessment is categorized into two classes: *pass* or *fail*.

Despite aiming for an unsupervised classification model, we had to perform a manual labeling of the data due to limited data. This would allow us to evaluate the accuracy of the model. Labeling was done by judging the alignment plots that were acquired during each observation.
As a first step of model creation, we identified relevant features, i.e. the parameters that make up a model. It enabled a comprehensive understanding of initial clusters within the data set. Caution is warranted in assessing certain features. For instance, while the optical power after alignment showed a high correlation with the labels, its reliability will depend on the circuit or component variation that is on the PIC.
It was found that the spot size of the coupled in- and output beams are the most promising feature because it is usually independent of the circuitry on the chip. This does however assume that the dimensions of the I/O are uniform across chips. For the current case, this is a valid assumption, because the same building block is used as an optical I/O for all the devices under test. The spot size is approximated by,

$$S \propto \sigma_{\text{lat}} \sigma_{\text{vert}}, \tag{1}$$

with $\sigma_{\text{lat}}$ and $\sigma_{\text{vert}}$ being the width of the Gaussian fit in the lateral and vertical direction, respectively. $S$ can be calculated on both sides of the chip for each observation. Figure 2a shows the spot sizes plotted against each other for all the measurements on tens of chips.

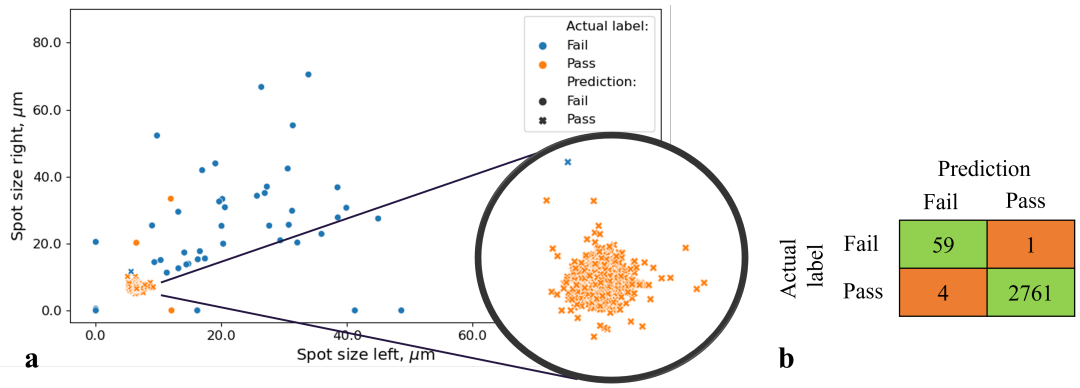


Figure 2: a—Spot sizes on the left and right I/Os against each other (2825 observations in total). The color indicates the manually assigned label while the shapes indicate the predicted label. b—The resulting confusion matrix of DBSCAN.

In the plot a distinct cluster can be seen, in this case centered around approximately 7 $\mu m^2$, surrounded by distant well separated outliers. This makes the spot sizes very suitable for using with a clustering algorithm. For that purpose Density-Based Spatial Clustering of Applications with Noise (DBSCAN) was used [6]. The DBSCAN algorithm identifies core points, which are data points with a minimal number of neighbors ($n_{\text{min}}$) within a specified radius ($\varepsilon$). Points that do not have enough neighbors but lie within the radius of a core point are considered border points. Data points with few or no neighbors are treated as noise or outliers. The main advantage of DBSCAN is that it can distinguish a range of cluster shapes since it is based on the density.
We have applied DBSCAN to the data from tens of InP PICs from two different wafers, 2825 observations in total. The $n_{\text{min}}$ and $\varepsilon$ parameters were systematically varied and their impact on model performance was monitored. The optimal combination was found to be

$n_{\min} = 20$ and $\varepsilon = 2$ and yielded the highest accuracy ($> 99.8\%$) across all measurements. From the confusion matrix (figure 2b) it can be seen that there are four false negatives and one false positive. The incorrect predictions could be due to the dubious manual labeling method. During revision it was found that the label was inconclusive. The potential for error in the personal judgement during the manual labeling process is likely and a better system is needed.
An additional metric is the silhouette score [7]. The silhouette score measures how well-defined the clusters are in the data. It calculates, for each data point, the average distance to all other points in a cluster and the smallest average distance to all points in the other cluster. The silhouette score ranges from –1 to 1, with –1 indicating incorrect clustering and 1 good clustering. For the clusters identified in figure 2 this resulted in a score of 0.97 which is an indication of highly dense clustering with distinct clusters. With proper data scaling, the algorithm could be expanded to any other material platform as long as the I/O dimensions are uniform across the chip design.

## Conclusions

In this paper, we have developed a ML-based method of reliable measurement data classification using the DBSCAN algorithm. The DBSCAN algorithm can sort measurement data with very high separation and accuracy, which was proven on 2.8k observations from our automated test setup (silhouette score of 0.97 and accuracy $> 99.8\%$). The outlined method may be expanded to all levels of the production chain (wafer, bar, die, package and module), thus laying a foundation for scalable and efficient testing. Future work will look at further refinements in the labeling procedure, broadening the current data set together with expanding the model with other features like stage movement and power parameters.

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