Machine Learning Analysis of 2×1 VCSEL Array Coherence and Imaginary Coupling Coefficient

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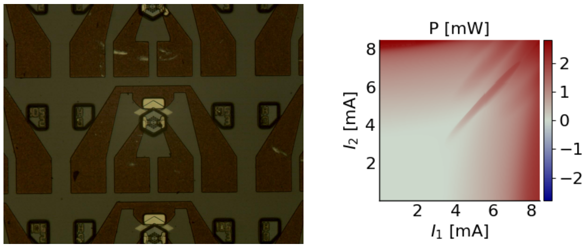
Abstract: Machine learning is used to estimate the coherent-coupling power enhancement from 2×1 VCSEL arrays and serves to identify coherent non-Hermitian operation.

1. Introduction

Photonic Crystal VCSEL arrays such as shown in Fig. 1a have demonstrated numerous novel static and dynamic properties that occur when the optical modes in the element cavities couple to each-other, ranging from increased output power and beam-steering to decrease noise [1] and higher modulation bandwidths [2]. The independent control of the injection current and thus gain in each of the coupled VCSEL elements enables the arrays to ve electronically adjusted to coherent operation [3] which produces non-Hermitian supermodes [4]. However, characterization of coherence in such lasers is nontrivial. Machine learning has been previously proposed for the analysis of transverse modes in individual lasers [5], and here we propose using it to assist in the analysis of mode coupling within laser arrays. We explore the application of machine learning (ML) methods to optical power measurements for VCSEL arrays to enable scalable automated identification of non-Hermitian supermode operation and determination of the imaginary coupling coefficient.



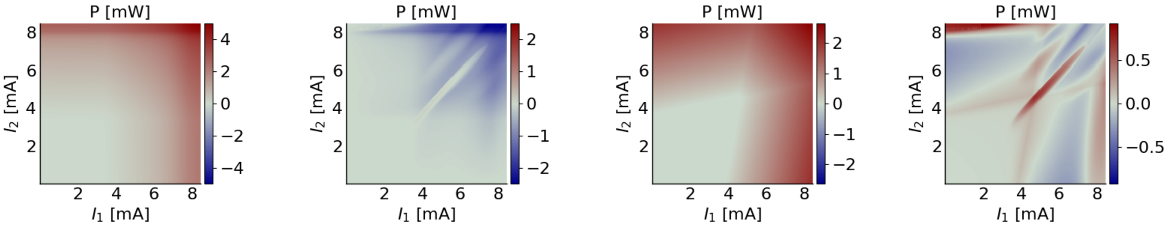
(a) Microscope image of a 2×1 VCSEL array

(b) Power as a function of dual driving current for a 2×1 VCSEL array.

Fig. 1

2. Methods and Analysis

The measured optical output power of a 2×1 VCSEL array as a function of driving current to either element is plotted in Fig. 1b. This power measurement shows an obvious "ridge" of increased power along the diagonal that is attributed to coherent coupling between the two element cavities. In order to estimate the power enhancement at each current set-point, we must have an estimate for the uncoupled array power. A simple "naive" estimate is simply the sum of the individual element powers, $P_{\text{uncoupled,est.}}(I_1,I_2) = P(I_1,0)+P(0,I_2)$.



(a) "Naive" uncoupled power estimate

(b) "Naive" power enhancement estimate

(c) ML uncoupled power estimate

(d) ML power enhancement estimate

Fig. 2: Using the naive uncoupled array power estimate to calculate the power enhancement.

We calculate the naive estimate for uncoupled array power and plot in Fig. 2a. The power enhancement is then estimating using this estimate in Fig. 2b. The naive estimate of the excess power is negative for almost all of the measured points, including the coherent ridge, indicating a major issue in this approach. The fatal flaw is that regardless of coherent coupling between the cavities, the two lasers have thermal cross-talk that leads to the output power of one cavity to be dependent on the injection to the other cavity, even in the uncoupled regime [3]. This necessitates a more sophisticated estimate of the uncoupled array power that incorporates these effects.

We use a dense neural network that predicts the total array power given a pair of driving current values ($2 \to 1$ mapping for a 2×1 array) that has been trained on the measured data. An appropriately designed network will estimate the uncoupled array power incorporating thermal shift effects but not coherent power enhancement, as shown in Fig. 2c. We use this machine-learning obtained estimate to calculate an improved estimate of the power enhancement, plotted in Fig. 2d. This estimate is better than the naive estimate for identifying the coherent region, which is now estimated to be a positive value. However, the uncoupled array power estimate still shows error (as evident by the non-zero values away from the coherent ridge in Fig. 2d) that further optimization of neural network design and training may reduce.

The neural network provides an estimate for the uncoupled array power P_{total}, and this quantity is subtracted from the measured total (coherently coupled) power to obtain the coherent power enhancement ΔP_{total}. This quantity also can be used to identify the coherently coupled regime, where the array produces low divergence beam-steering and operates with enhanced modulation bandwidth. Literature relates the magnitude of the imaginary component of the coupling coefficient as proportional to coherent power enhancement, $|\kappa_i| \propto \frac{\Delta P_{\text{total}}}{a+P_{\text{total}}}$ for some constant a [6].

3. Conclusion

Preliminary results show that machine learning can provide an improved estimation of the uncoupled array optical power from measured data enabling improved estimation of the power enhancement. The power enhancement may enable automated identification of coupled operation in VCSEL arrays, enabling enhanced power, beam, and modulation performance, and is an essential term in determining the imaginary term of the coupling coefficient.

References

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