Computational Techniques for Optimization and Design of InGaAlAs MQW Lasers

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***Abstract*—Semiconductor lasers present several challenges in terms of both design and understanding. Their numerous epitaxial layers, material properties, and physical structures generate a complex and high-dimensional space of parameters that must be optimized. We develop and demonstrate the use of a computational model capable of exploring this high-dimensional space. We validate this model against experimentally obtained data to ensure high-quality inputs are generated for use in future machine learning analyses.**

Keywords—Fabry-Perot, buried heterostructure, multi-quantum well, machine learning, model validation

I. Introduction

Semiconductor lasers have become ubiquitous in today's technological and scientific industries. Diode lasers are key components in telecommunication, power-beaming, and sensors [1], [2], [3]. The wide-range of applications creates a high number of possible designs to select from, presenting a challenge for laser designers who must not only select the appropriate design parameters for the application but must then optimize the design to maximise the relevant performance metrics.

Techniques for optimization of various types of lasers have included genetic algorithms, binary search, simulated annealing, and Bayesian methods [4], [5], [6]. These techniques are useful for finding optimal conditions for device design or best fits in large parameter spaces. While these methods are valuable for model validation and extracting physical parameters they may not be the most efficient choice for developing novel designs or providing a physical understanding of device performance (i.e. "knowledge discovery"). Other methods employing machine learning (ML) techniques, such as neural networks [7], have been suggested. In particular, dimensionality reduction methods such as principal component analysis (PCA) [8], [9], can significantly reduce the complexity and computational cost of laser design studies by reducing the dimensionality of the problem and offering interpretability.

Nonetheless, in order to facilitate the use of ML techniques, it is important to ensure that training data is based on a validated device model in order to produce physically meaningful results. Therefore, optimization techniques to fit data to experiment still play an important role. We present a model of a Fabry-Perot (FP) buried heterostructure (BH) laser that is calibrated to experimental results. The model will be used as a foundation for future ML applications.

II. Methods

A. Experimental

We perform measurements of LIVs, spectrum, and net optical gain on FP-BH lasers. The devices are grown on InP substrates. The active region consists of four multi-quantum well layers composed of compressively strained InGaAlAs. The lasers have cavity lengths of 2 mm.

The lasers are mounted on a temperature-controlled stage and the net optical gain is measured at temperatures of 20 °C, 35 °C, and 50 °C. The gain is measured just below the threshold current (I_{th}) of the laser at 17 mA, 22 mA, and 29 mA for each respective temperature. These measured curves are shown in Fig. 1. The method follows that of Ref. [10].

B. Modelling and Numerical Optimization

We combine commercially available laser simulation packages with Python tools to simulate and study the BH lasers. The measurements described in Section II.A are used to validate the model. The commercially available software packages are Photon Design's Harold and PICWave. In Harold we generate the material gain (G_{mat}) of the BH laser modeled as a 1-dimensional epitaxial stack. This is followed

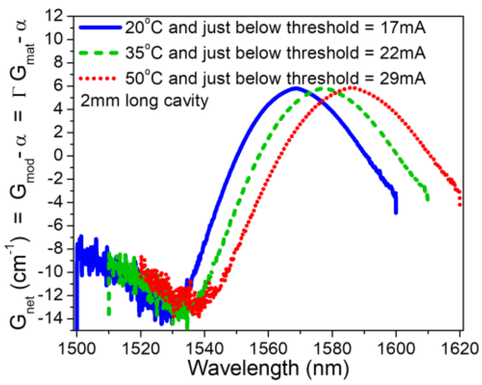

Fig. 1. Experimental G_{net} curves for an FP-BH laser with four quantum well layers. Measurements are performed on a temperature controlled stage at 20 °C, 35 °C, and 50 °C. Measurements are performed just below the I_{th} of the laser.

by simulations in PICWave which returns the modal gain (G_{mod}), confinement factor (Γ), modal loss (α) and calculates the LIV curve. The net gain and LIV curves are extracted and compared with the experimental data.

These two standalone software packages are tied together to provide uninterrupted flow of the simulations using Python, facilitating data extraction in order to fit the data and validate the model.

We select five material properties as fitting parameters: the scattering loss of the laser cavity, the electron and hole net recombination lifetimes, the intraband lifetime, and the bandgap narrowing factor in the QW regions. A differential evolution algorithm [11] is used to narrow down the initial parameter space. The best solution is further refined using a Nelder-Mead algorithm. The residual is the root sum of squares of I_{th} and the differential efficiency (η_d).

III. Results and Discussion

We report the final values of the fitting parameters for the scattering loss of the laser cavity, the electron and hole net recombination lifetimes, the intraband lifetime, and the QW bandgap narrowing factor as 8.6 cm^{-1}, 9.4e-12 s, 4.1e-13 s, 7.9e-14 s, and -1.3e-9 respectively. The results of this best fit to the 2 mm cavity BH laser with four quantum well layers operating at 20 °C are shown in Figure 2. The fitting was performed against the root sum of squares of the η_d and I_{th}. Experimentally we observe an I_{th} of 16.852 mA and a η_d of 0.116 W/A under continuous wave operation. The optimizer returns a result of 16.859 mA and 0.115 W/A for these parameters respectively. We note that there is good agreement between the experimentally extracted cavity mode loss 14.03 cm^{-1} and the mode loss generated by the simulations 15.02 cm^{-1}. The net gain also shows good agreement between

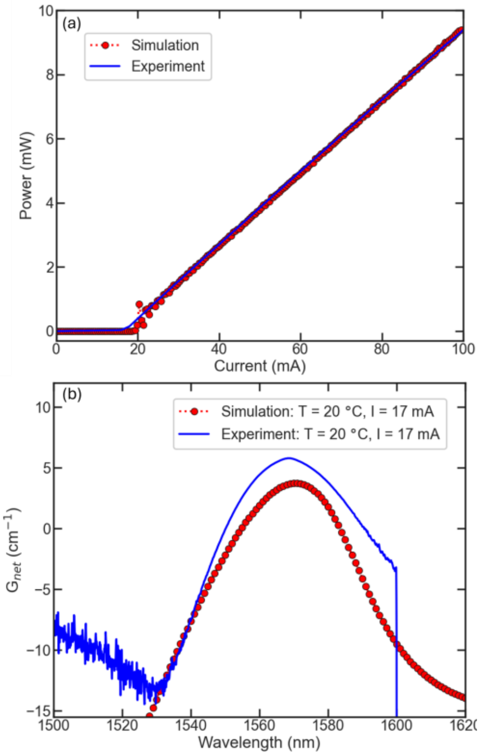

Fig. 2. The (a) simulated and experimental LIV and (b) G_{net} for a 2 mm cavity FP-BH laser. Both experimental gain measurements and simulated results were performed with a substrate temperature of 20 °C and a drive current of 17 mA.

experiment and simulation with respect to the gain peak. This gives further weight to our model validity since neither the modal loss nor the gain were considered in the residual calculations but were instead extracted as a result of the fitted simulations. Further agreement between the modal loss and the gain could be obtained by defining a figure of merit that includes these elements.

The validated material parameters provide confidence in the simulation outcomes of these FP-BH lasers and will be used as a foundation for future machine learning techniques in combination with the process flow we have detailed here.

IV. Conclusions

We present a validated model of an FP-BH laser grown on InP substrates with four InGaAlAs quantum well layers. The simulation process flow combines multiple software packages (Photon Design's Harold and PICWave) as well as in-house techniques implemented through Python to extract simulation results and parameters to accurately fit the experimental data. A differential evolution algorithm is used to assess five different material parameters. The solution is refined with a Nelder-Mead algorithm. We achieve a robust fit to the data, ensuring high quality inputs are available for further study using machine learning analyses.

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