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Machine Learning Assisted Extraction of Vertical Cavity Surface Emitting Lasers Parameters

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Abstract

We propose a machine learning-based framework to extract circuit-level VCSEL model parameters. The proposed approach predicts the parameters exploiting the light-current curve and small-signal modulation responses with two steps at constant and variable temperature, respectively. Promising results are achieved in terms of relative prediction error.

Keywords

Vertical Cavity Surface Emitting Lasers, Machine Learning, Parameters extraction, Circuit-level models, Deep Neural Network.

I. INTRODUCTION

In the last decades, many computationally efficient models have been introduced to describe both stationary and dynamic Vertical Cavity Surface Emitting Lasers (VCSEL) behaviors accurately. These models play a fundamental role in understanding the VCSEL physical properties, allowing further optimizations of these devices. Along with this, they are also an essential resource for performing a realistic simulation of VCSEL sources as part of larger optoelectronic systems. Indeed, so-called ”circuit-level models” of VCSEL are available in simulation tools such as Synopsys OptSim circuit simulation environment [1]. However, in these models, many physical parameters must be appropriately set to accurately reproduce the behavior of existing laser sources, which is a necessary step to obtain correct results from the numerical simulation of a whole photonic system. The extraction of these unknown physical parameters from experimental curves is generally time-consuming and relies, e.g., on trial and error approaches or regression analysis. In this scenario, we propose a Machine learning (ML) based approach to the problem, which is able to extract the required VCSEL parameters from experimental data effectively.

II. VCSEL MODEL

The considered VCSEL model, available as a standard OptSim block, is an extension of the model originally proposed in [2] to include the temporal evolution of the field phase [3]. In cylindrical geometry, the carriers number is expanded in Bessel series and the first two terms N_0 and N_1 are considered [4]. Assuming spatially independent rate equations, Eq.s 1-4 can be introduced for the temporal evolution of the carriers N_0 and N_1, the photons number S and the phase ϕ, with I injected current, q electron charge, I_l leakage current, ϕ_{100} and ϕ_{101} overlap coefficient, $beta$ spontaneous emission coefficient, α linewidth enhancement factor. In order to model the dependence of the VCSEL behavior with respect to temperature T, a phenomenological representation of the gain G and the carrier transparency number N_t is introduced based on fitting parameters, as shown in Eq.s 5-6 [2]. Other parameters introduced in Eq.s (1-6), objective of the ML study, are finally defined in Tables I and II.

$$\frac{\mathrm{d}N_0}{\mathrm{d}t} = \frac{\eta_\mathrm{i} I}{q} - \frac{N_0}{\tau_\mathrm{n}} - \frac{G\left[\gamma_{00}(N_0 - N_\mathrm{t}) - \gamma_{01}N_1\right]}{1+\varepsilon S}S - \frac{I_\mathrm{l}}{q} \quad (1)$$

$$\frac{\mathrm{d}N_1}{\mathrm{d}t} = -\frac{N_1}{\tau_\mathrm{n}}(1 + h_\mathrm{diff}) + \frac{G\left[\phi_{100}(N_0 - N_\mathrm{t}) - \phi_{101}N_1\right]}{1+\varepsilon S}S \quad (2)$$

$$\frac{\mathrm{d}S}{\mathrm{d}t} = -\frac{S}{\tau_\mathrm{p}} + \frac{\beta N_0}{\tau_\mathrm{n}} + \frac{G\left[\gamma_{00}(N_0 - N_\mathrm{t}) - \gamma_{01}N_1\right]}{1+\varepsilon S} \quad (3)$$

$$\frac{\mathrm{d}\phi}{\mathrm{d}t} = \frac{\alpha}{2}\frac{G\left[\gamma_{00}(N_0 - N_\mathrm{tr}) - \gamma_{01}N_1\right]}{1+\varepsilon S} \quad (4)$$

$$G(T) = G_0\left(a_\mathrm{g0} + a_\mathrm{g1}T + a_\mathrm{g2}T^2\right) / \left(b_\mathrm{g0} + b_\mathrm{g1}T + b_\mathrm{g2}T^2\right) \quad (5)$$

$$N_\mathrm{t}(T) = N_\mathrm{tr}\left(c_\mathrm{n0} + c_\mathrm{n1}T + c_\mathrm{n2}T^2\right) \quad (6)$$

III. MACHINE LEARNING AND DATASET GENERATION

The proposed analysis focuses the extraction of 18 parameters listed in Tables I and II. The complexity of the analysis is reduced by executing it in a two-step approach, which requires the training of two smaller ML agents mainly based on a Deep neural network (DNN) architecture having three hidden layers with ten neurons per layer [5]. The proposed DNN model used ReLU as an activation function and Mean square error (MSE) as a loss function. The DNN model is configured for 100 training steps with a default learning rate of 0.01. The training and test set proportion is 70% and 30% of the total dataset.

The first DNN agent is trained using data generated at a constant temperature and is used to extract the experimental data parameters reported in Table I. In particular, a dataset of 10 000 simulations is created at the constant temperature of 25 °C, changing the values of parameters listed in Table I and keeping all the other parameters fixed; parameters appearing in Table II

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