Dynamic Response Prediction of Bi-State Emission of Quantum Dot Lasers Based on Extreme Learning Machine

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Abstract—**Dual-state emission is an phenomenon which takes place in Quantum Dot Lasers at different temperature and operating conditions. In this study, we investigate that issue from a nonlinear regression model based on Extreme Learning Machine, which revealed to be able to predict the spectrally resolved transient response of InAs/InGaAs quantum dot laser with error performance as low as 0.54%.**

Index Terms—**quantum dot laser, optical filters, extreme learning machine, multilayer perceptron.**

I. INTRODUCTION

Quantum Dot Laser (QDL) is an important class of semiconductors with distinct properties, as sharp optical transitions, low threshold current, high output power and large modulation bandwidth. Thus, it has application in several areas like medicine, telecommunications and optical instrumentation.

Most of its interest comes from the carrier dynamics, which gives rise to the Dual-State Emission (DSE), at certain operating conditions. The DSE consists of the optical power emission in two spectral regions: one around the Ground State (GS) and the other around the first Excited States (ES) [1]. That is useful for applications requiring wide emission spectrum.

In this work, we discuss the issue of DSE in time-domain, but from the perspective of nonlinear regression based on artificial neural networks (ANN), in this case, the Extreme Learning Machine Networks (ELM) [2]. The model can optically filter the switch-on transient of QDL total output power into the one corresponding to the spectral region around GS and the other one, around the first ES. Hence, it can help to develop the electronics of low-resolution optical filters in those applications in which an optical spectrum analyzer is not a choice for cost issues and only power meters are available.

II. THEORY

A. Extreme Learning Machine

A possible application for artificial neural networks is the modeling of nonlinear dynamic systems, such as QDL, whose interaction between carriers is admittedly complex and have been object of research in last years [3], [4].

One example of ANN is the ELM, a learning technique for training Single Hidden Layer Feed-Forward Neural Networks. The main difference between ELM and other ANN models is its the significant increase in training speed through random generation of input weights and the bias of the hidden layer [2], as defined by:

$$f_L(x) = \sum_{i=1}^{L} \beta_i h_i(x) = h(x)\beta \qquad (1)$$

$$h_i(x) = G(a_i, b_i, x) \qquad (2)$$

$$\beta \in \mathbb{R}^{Lxm^{min||H\beta - T||^2}} \qquad (3)$$

$$\beta^* = H'T \qquad (4)$$

where $\beta = [\beta_1, ..., \beta_L]^T$ is the weight vector that connects the hidden layer with L nodes and the $m \geq 1$ output nodes; $h(x) = [h_1(x), \ldots, h_L(x)]$ is the nonlinear mapping function; $G(a_i, b_i, x)$ (with the parameters of hidden nodes (a, b)) is a nonlinear continuous function; H is the output matrix of the hidden layer (randomly generated); T is the training data matrix; $||.||$ is the Frobenius method; H' denotes the Moore – Penrose generalized inverse matrix of H.

III. METHODOLOGY

A. Characteristics of Experimental Data

The study used measurements made available by the Semiconductor Optics Group of the Technical University of Darmstadt. It consists of 147 time-series (sized 510 samples) of switch-on transient of InAs/InGaAs QDL separated into GS, ES and total output power as well. Essentially, they came from experiments of electrical current step response at different temperatures, in which the upper level changed progressively up to 139.9 mA (@ 20 ^{o}C) and up to 185 mA (@ 40 ^{o}C).

B. Proposed Model

The regression model proposed consists in an ANN which implements the nonlinear function ϕ in Eq. (5); it represents the mapping from the input space containing the total optical power, $P(n)$; the driving electrical current, I; the operating temperature, T; and the time-vector, $t(n)$; to the output space containing the GS and ES optical power at each discrete time instant, n. In turn, Eq. (6) describes the input optical power, $P(n)$, and shows the model needs a memory of $n-k$ samples of the total power to support the time-series prediction.

$$P^{GS}(n), P^{ES}(n) = \phi(P(n), I, T, t(n)) \tag{5}$$

$$P(n) = P^T(n), P^T(n-1), ..., P^T(n-k) \tag{6}$$

C. Design parameters and performance validation

To determine the quantity of the delayed input samples in Eq. (6), k, we calculated the autocorrelation and the partical autocorrelation functions of the vector $P(n)$ and observed that the range $1 < k < 5$ has the maximum correlation.

Another parameter investigated was the size of the hidden layer, which ranged from 2 to 1,000 with sinusoidal activation function for ELM. For completeness, we used the classical Multilayer Perceptron (MLP) [5] with size ranging from 2 to 50 neurons and Levenberg-Marquardt training function. Additionally, the data were normalized and grouped into training (70%) and testing (30%) samples to develop the models.

For what concerns model validation, we used widely known performance parameters such as RMSE (Root Mean Square Error) and MAPE (Mean Absolute Percentage Error).

IV. RESULTS AND DISCUSSION

The Table 1 shows the evaluation of the best results obtained for each of the proposed configurations. The worst result is with RMSE of 11.30 μW and MAPE of 1.72%, low, so, enabling the application of the model in any verified scenarios.

The ELM Model also has error lower than MLP for all quantities of delayed input powers and its best overall result has error 60% lower than that presented by MLP, showing its superiority for this application.

In addition, the Figure 1 shows the experimental and theoretically predicted time-series of a switch-on transient experiment with $I = 123\ mA$ at 20 ^{o}C (a), and $I = 174\ mA$ at 40 ^{o}C (b). The rather good agreement between the solid (experimental) and dashed lines (predicted by the model), which we stress was obtained for a small input memory lag ($k = 2$) suggests that the proposed approach is a good candidate for the embedded electronics of low-resolution spectral analyzers.

V. CONCLUSIONS

The alternative of filtering the QDL optical power from ANN model is promising, with ELM and MLP very low prediction errors. As future work, we will investigate a case of higher spectral resolution at least in continuous-wave operation, checking the ability of the inference machine to predict different lasing lines around the GS and ES. The experimental data necessary for this investigation is available and is currently under preparation.

TABLE I
PERFORMANCE EVALUATIONS OF THE BEST RESULTS

ANN Model	Qty. of Delayed Input Powers	Hidden Nodes / Neurons	RMSE (μW)	MAPE (%)
Extreme Learning Machine (ELM)	0	993	11.30	1.72
	1	811	2.99	0.55
	2	737	2.89	0.54
	3	232	3.91	0.77
	4	270	4.07	0.77
	5	141	5.08	0.95
Multilayer Perceptron Network (MLP)	0	48	8.40	1.32
	1	44	8.60	1.52
	2	50	9.00	1.67
	3	45	9.00	1.64
	4	47	8.97	1.60
	5	47	9.08	1.71
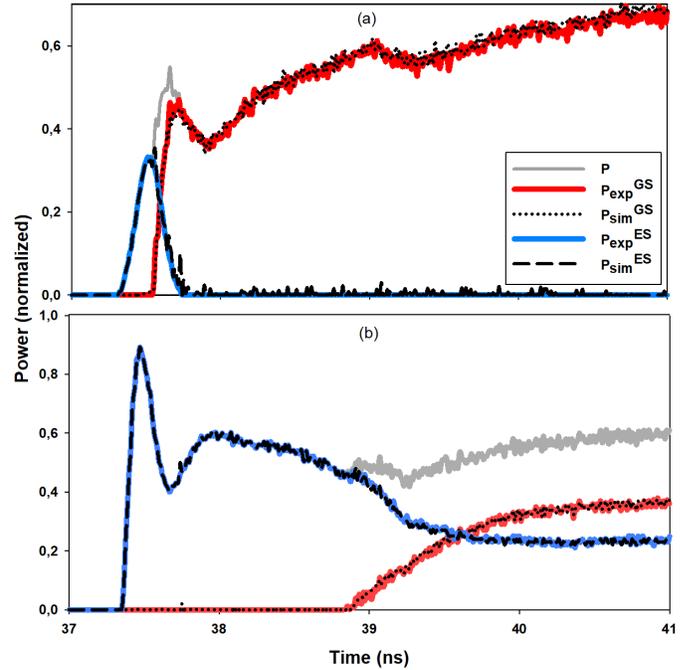
Fig. 1. ELM model time-response with (a) I = 123 mA at 20 ºC and (b) I = 174 mA at 40 ºC, where P is the QDL Optical Power; P_{exp}^{GS} and P_{sim}^{GS} are the Ground State Power, experimental and simulated, respectively; P_{exp}^{ES} and P_{sim}^{ES} are the Excited State Power, experimental and simulated, respectively.

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