MODELING TEMPERATURE DEPENDENT NONLINEARITY IN A LASER DIODE USING FUZZY LOGIC

N. Vijayakumar* and Nisha S. Nair

Fiber Optics & Photonics Lab, Department of Electronics and Communication Engineering
College of Engineering, Trivandrum, India 695 016
Tel: 09387808905; E-mail: dr.nvkr@gmail.com

Abstract - Modeling of non-linear behavior of a laser diode is carried out in this paper. A combined approach of fuzzy logic and neural network is used. An Adaptive Neuro-Fuzzy Inference System (ANFIS) based model is trained using experimental data. Theoretical analysis of temperature dependent nonlinearity becomes complex as it requires simultaneous consideration of mechanisms like Auger recombination, Inter Valence Band Absorption (IVBA), thermionic carrier emission out of the active region, lateral carrier spreading, passive layer absorption, spontaneous recombination within passive layers and optical gain reductions. An ANFIS based model presented in this paper accounts for this temperature dependent nonlinearity. Once the model is trained it computes the Total Harmonic Distortion (THD) and the power output for various drive currents and operating temperatures. The validation of the model using experimental data yields a Mean Squared Error (MSE) of 2.35x10^-4

Index Terms - Fuzzy logic, Direct modulation, Rate equations, Temperature dependent nonlinearity, Total Harmonic Distortion.

I. INTRODUCTION

Over the last few decades tremendous developments in semiconductor technology has led to incredible improvements in the direct modulation performance of laser diodes, with a notable increase in bit rate of optical transmissions. The availability of high-speed lasers has stimulated a variety of applications in communications and signal processing. Various experiments demonstrating optical fiber transmission at very high bit rates over long distances were reported [1-3]. Other applications of high-speed lasers include optically controlled microwave switches [4], optical injection-locking of electronic oscillators [5] and optical delay-line filter networks [6]. Recently microwave fiber optic links enjoy much attention due to their potential application in wireless networks [7]. The microwave fiber optic link can carry several wide band radio channels, in a sub carrier multiplexed system. Direct modulation of the laser provides a cost effective solution for transmission in such links. The principle attraction of the direct modulation technique is its simplicity. With the laser biased above threshold and a modulation signal superimposed on the drive current, the output optical power of the laser is an analog of the modulation waveform. The radio over fiber links in wireless access suffers from performance degradation due to optical transmitter nonlinearity. Semiconductor laser diode nonlinearity generates distortions of inband, harmonic and inter-modulation in modulating RF signals. Modulation techniques such as multilevel Quadrature Amplitude Modulation (QAM) are of greater interest for future mobile communication systems because of their high spectral efficiency. In QAM, the baseband information is transmitted by modulating amplitude and phase of the carrier. This makes such a modulation technique highly sensitive to Laser Diode (LD) nonlinearity. Hence various linearization methods have been studied and performed on the linearization of LDs [8-9]. In a directly modulated laser, the
main source of distortion is caused by the intrinsic nonlinearities of the laser which limits the dynamic range and hence the system performance. Any nonlinear distortion generated by the semiconductor laser such as intermodulation distortion can also give rise to interchannel interference which degrades the quality of the received signal. The linearization methods such as negative feedback, optical feed forward, quasi-optical feed forward and phase shift is proposed. Adaptive digital pre distortion technique seems to be a promising approach for the same, since it is simple and cost effective. This linearization requires a prior study of the nonlinearity of laser diodes, but conventional analytical model based on rate equations fail to account for the nonlinear behavior. Here we propose a new nonlinear, modeling technique based on Adaptive Neuro-Fuzzy Inference System (ANFIS) [10]. We choose a long wavelength InGaAsP laser diode with a peak emission at 1550 nm. A data driven approach where the fuzzy rules are framed from the input-output data sets is used. The Takagi-Sugeno-Kang (TSK) Fuzzy Inference System (FIS) is suitable for generating fuzzy rules from a given input-output data set in a data-driven fashion [11].

Section 2 of the paper describes an analytical model of a laser diode based on rate equations. Section 3 introduces the basic concept of ANFIS and in section 4 we propose a neuro fuzzy based model to depict temperature dependent nonlinearity of laser diodes. In section 5 we discuss the model validation and the results obtained from the model.

II. ANALYTICAL MODEL

A popularly used mathematical model for laser diode is based on rate equations [12]. The laser diode rate equations are given in equations (1) and (2) where $N$ is the electron density, $S$ is the photon density, $\Gamma$ is the optical confinement factor given by the ratio of the active region volume to the modal volume, $g_0$ is the gain slope constant, $N_{ox}$ is the electron density at which the net gain is zero, $\tau_p$ is the photon life time, $\tau_n$ is the electron life time, $\beta$ is the fraction of spontaneous emission coupled into the laser mode, $V_{act}$ is the volume of the active layer, $q$ is the electronic charge, and $I_A$ is the current injected into the active layer. The parameter $\varepsilon$ is a small number (with units of volume) which specifies the gain compression of the active region. Typically the gain compression is small and the product $\varepsilon S$ has a value of a few percent at maximum drive current. Even this small level of gain compression has a dramatic effect on the dynamic response of the laser. The output power per facet is $P = SV_{act} \eta h \nu / 2 \Gamma \tau_p$, where $\eta$ is the quantum efficiency of the intrinsic laser and $h$ is Planck’s constant. In the rate equations (1) and (2) above, $N$ and $S$ are assumed to be constant across the active layer. This is a reasonable approximation for narrow-stripe lasers with strong confinement of the injected carriers.

The performance of long-wavelength InGaAsP/InP laser diodes is known to be strongly temperature dependent. Self-heating or ambient temperature elevation causes the threshold current to increase and the slope efficiency to decrease. The physical mechanisms dominating the temperature sensitivity includes Auger recombination[13], Inter Valence Band Absorption (IVBA)[14], thermionic carrier emission out of the active region[15], lateral carrier spreading[16], passive layer absorption[17], spontaneous recombination within passive layers[18] and optical gain reductions[19]. The temperature sensitivity of the threshold current is dominated by Auger recombination at lower temperatures and by vertical leakage at higher temperatures. Simultaneous consideration of all these mechanisms that account for temperature dependence on the laser diode performance makes the analysis very complex. The proposed ANFIS based model is an alternate approach for...
modeling temperature dependent nonlinearity of laser diode alleviating this complexity.

III. FUZZY INFERENCE SYSTEM

Basically a fuzzy inference system is composed of five functional blocks. (Fig. 1)

- a rule base containing a number of fuzzy if-then rules
- a database which defines the membership functions of fuzzy sets used in fuzzy rules
- a decision-making unit which performs the inference operations on the rules
- a fuzzification interface which transforms the crisp inputs into degrees of match with linguistic values
- a defuzzification interface which transform the fuzzy results of inference into a crisp output.

Two most common fuzzy inference systems are the Mamdani fuzzy model [14] and Takagi-Sugeno-Kang (TSK) model [11]. The major difference between them is that the consequences of rules in TSK FIS are represented by functions of the input variables whereas those in Mamdani FIS are represented by fuzzy sets or linguistic variables. In the TSK model, the final result is just a weighted summation of consequence values obtained from each mathematical model. But in the Mamdani model, the final result is a summation of level sets and needs to be defuzzified by an appropriate method [20]. The defuzzification process can be rather computationally expensive, though the Mamdani model gives better knowledge or linguistic transparency in the rule consequent part.

The TSK FIS is used in this work to generate the initial rule base, because the TSK model is suitable for generating fuzzy rules from a given input-output data set in a data driven fashion.

Let \( X = (x_1, x_2, ..., x_p) \) denote an input vector to the model where \( x_1, x_2, ..., x_p \) denotes the model parameter values, then the typical TSK FIS consists of IF-THEN rules where the consequent parts are constant (zeroth-order) or linear function (first-order) of inputs and has the form

\[
R_i : \text{IF } x_i \text{ is }MF_{i1} \text{ and } ..., x_i \text{ is }MF_{ip} \text{, THEN } y_i = b_{i1}x_1 + ... + b_{ip}x_p + b_{i(p+1)}
\]

\( l = 1, 2, ..., M \) \( M \) is the number of fuzzy rules, \( y_i \) is the output of the \( l \)th rule. \( MF_{i1}, ..., MF_{ip} \) are the antecedent fuzzy sets. The overall output of the model is computed as

\[
y = \frac{\sum_{l=1}^{M} w_i y_i}{\sum_{l=1}^{M} w_i}
\]

where \( w_i \) is the degree of
activation of the antecedent in the $l^{th}$ rule and,

$$w_i = \prod_{l=1}^{P} F_{il}(x_i), \quad l = 1, 2, \ldots, M$$

Throughout the work, we adopt a product composition for and operation and min inference, which are most commonly used composition and inference methods in engineering applications.

In this work we first hypothesize a parameterized system based on the TSK model. After the rule base is set, fine tuning of the parameters is needed. The initial model is not optimal because the membership functions (MF) of the antecedents in the rules are established from the partition of the input data only; accordingly, the model cannot appropriately represent the input-output relationship. In this paper, an Adaptive Network based Fuzzy Inference System is adopted for the fine tuning of the parameters. ANFIS, first reported in [10], uses information processing and learning capability of distributed neurons as well as fuzzy logic to determine the actual model of the device.

IV. PROPOSED MODEL

A collection of experimental data is required to train the ANFIS based model and to capture the system characteristics accurately. The best way to study the characteristics of a device is to collect experimental data that can be used in constructing adaptive models. The behavior of the laser diode simulated using rate equations does not take into consideration the nonlinearity. Using the experimentally obtained input/output data set, we construct a fuzzy inference system (FIS), whose membership function parameters are tuned using the error reduction algorithms. This allows the fuzzy systems to learn from the data they are modeling.

Fig. 2 shows the proposed neuro-fuzzy model where the temperature ($T$), drive current ($I_D$) and the peak to peak modulating current amplitude ($I_{pp}$) are identified as input parameters and power output ($P_0$) and Total Harmonic Distortion (THD) are identified as the output parameters.

A network-type structure similar to that of a neural network, which maps inputs through the input membership functions and associated parameters, and then through the output membership functions and associated parameters to outputs, can be used to interpret the input-output map.

The parameters associated with the membership functions will change through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector, which provides a measure of how well the fuzzy inference system (FIS) is modeling the input/output data for a given set of parameters. Once the gradient vector is obtained, an optimization routine can be applied in order to adjust the parameters, so as to reduce the error measure defined by the sum of the squared difference between actual and desired outputs. First, the parameters of the MFs in the antecedent are optimized by the gradient descent method (back propagation algorithm). Once the antecedent parameters are fixed, the consequent parameters are estimated by least square method.

V. RESULTS AND DISCUSSIONS

The power output of a 1550 nm InGaAsP laser diode was measured experimentally for various values of drive currents and operating temperatures (in the range 20$^\circ$C to 32$^\circ$C). The P-I curve characterizes the emission properties of a semiconductor laser. It also indicates the threshold level. The P-I characteristics obtained from the model shows the laser diode has a threshold current of 0.598 mA at 24$^\circ$C. This value of threshold current is found to increase with temperature as shown in Fig. 3 and Fig.4. The Fig. 4 shows the results in Fig. 3 but in a sensitive scale.
The threshold current is found to be 0.605 mA at 28°C and 0.612 mA at 32°C. The analytical model based on rate equation account for this increase in the threshold current with temperature. However it fails to explain the influence of temperature dependent nonlinearity on the THD of the LD. The proposed model takes into account the temperature dependent diode nonlinearity and computes THD and power output at given temperature, peak to peak modulating current and drive current.

The ANFIS based model is trained using experimental data. The input-output data obtained experimentally were separated into two sets. One set was used for training the FIS based model (indicated with ‘*’ in Fig. 4) and the other set was reserved for model validation (indicated with ‘o’ in Fig. 4). The solid lines in the figures indicate the values generated by the model. The results obtained were in good agreement with experimental test data. The MSE is found to be 1.63x10^{-4}. The slope efficiency of the laser diode is found to be decreasing with the operating temperatures as depicted in Fig. 4. This decrease can be attributed to junction heating occurring under continuous wave operation. In our work, the drive current frequency was kept at 1 MHz and the laser diode was biased at 630 µA. Superimposing the modulating current on bias current the output obtained was distorted due to diode nonlinearity as shown in Fig. 5.

The THD was computed for different values of input peak to peak modulating current. The distorted power output was sampled and THD was estimated from Fourier coefficients using Fast Fourier Transform (FFT) algorithm. The harmonics up to sixth order were found to be significant with second and third order ones dominant.

The experiment was repeated for different values of peak to peak modulating drive current without changing the bias current. The results are shown as data points in figures 6 and 7.
temperature dependence of nonlinearity in a laser diode. The proposed model for a laser diode with the THD and power output as output parameters can be used to study the nonlinear behavior of a laser diode. It depicts the influence of bias point, modulating signal swing and temperature on diode nonlinearity. Since this model relies on the experimental observations the disadvantages of using analytical models are evaded.

REFERENCES


