# An accurate optical gain model using adaptive neuro-fuzzy inference system

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This paper presents a single, simple, new and an accurate optical gain model based on adaptive neuro-fuzzy inference system (ANFIS) which combines the benefits of Artificial Neural Networks (ANNs) and Fuzzy Inference Systems (FISs). The dynamic optical gain model results are in very good agreement with the previously published experimental findings.

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## 1. Introduction

The computer aided design (CAD) models are useful tools to evaluate the system performance at the design stage. Optical gain is one of these kinds which include important knowledge about the evaluation and operating characteristics of the laser diodes (LDs). For this reason, accurate and dynamic optical gain models are always required.

The optical gain is defined as the fractional increase in photons per unit length. This is also called the modal gain ($g_m$), though it is the material gain (g) which is attained from many calculations by using different theories, assumptions and rough estimation of parameter values. They are related by the optical confinement factor $\Gamma$ by the relation $g_m = \Gamma g$. However, the net modal gain in terms of quantum well number is equal to $g_m = N\Gamma g - \alpha_{tot}$, where N is the number of quantum-wells (QWs), $\Gamma$ is the optical confinement factor per well and $\alpha_{tot}$ is the combination of intrinsic and transmission losses. For an expanding rate of applications, an understanding of the optical gain spectra is very significant in order to obtain a dynamic model with predictive capability for the gain spectra of a specific laser diode structure.

There are different approaches in terms of optical gain for theoretical [1] and experimental sides [2]. Theoretical calculations usually require a large amount of computational time. On the other hand, numerous different and widely used experimental techniques proposed for optical gain which provides different advantages and disadvantages [2]. However more reliable measurement techniques are still needed.

There are successfully implemented previous models for GaAs QW LDs [3], InGaAsP QW LDs [4], InGaAs QW LDs [5], temperature measurement system [6] and linewidth enhancement factor [7] with ANNs, which is presented in literature. In this work, a new method based on the ANFIS [8] for the modelling of net modal peak gain of GaInP LDs with respect to different number of QWs and different injection levels is presented (Fig. 1). Different membership functions (MFs) with different network configurations are used in order to minimize the root mean square (rms) errors in terms of the ANFIS structure. The model completely agrees very well with the experimental results [9].

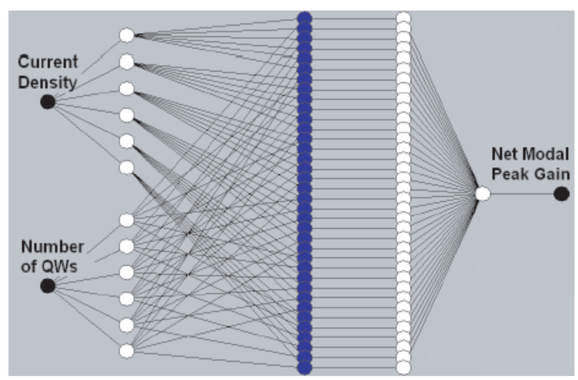


*Fig. 1. ANFIS model structure*

## 2. ANFIS modelling

ANFIS is a technique for automatically tuning Sugeno-type inference systems based on training data. It combines the benefits of ANNs and FISs. It maps inputs through input membership functions and associated parameters, and then through output membership functions to outputs. MF is a function that specifies the degree to which a given inputs belongs to a set or is related to a concept.

For simplicity, it is assumed that the ANFIS under consideration has two inputs, x and y, and one output, z. To present the ANFIS architecture, four fuzzy rules based on a first-order Sugeno model can be expressed as [10]:

Rule 1: IF x is $A_1$ and y is $B_1$ THEN $z_1 = p_1x + q_1y + r_1$
Rule 2: IF x is $A_2$ and y is $B_2$ THEN $z_2 = p_2x + q_2y + r_2$
Rule 3: IF x is $A_3$ and y is $B_3$ THEN $z_3 = p_3x + q_3y + r_3$
Rule 4: IF x is $A_4$ and y is $B_4$ THEN $z_4 = p_4x + q_4y + r_4$

where x and y are the crisp (well-defined) inputs. $A_i$ and $B_i$ are the fuzzy sets (linguistic labels as short, medium, tall etc.), $z_i$ are the outputs, $p_i$, $q_i$ and $r_i$ are the exact constants. To put it in a different way, they are linear parameters of the nodes in the then part of fuzzy if-then rules, and are called consequent parameters.

One possible ANFIS architecture to implement these four rules is shown (Fig. 2). The architecture of ANFIS consists of five layers. A circle indicates a fixed node whereas a square indicates an adaptive node (the parameters are changed during training).

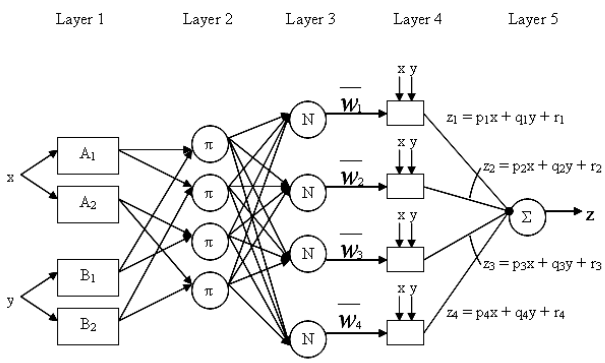


*Fig. 2. ANFIS structure for two-input Sugeno fuzzy model with four rules.*

**Layer 1:** Parameters in this layer are changeable. The outputs of layer 1 are the fuzzy membership grade of inputs. In the following presentation $O_{Li}$ denotes the output of node i in a layer L. Here $O_{1i}$ is denoted as the output of the i$^{th}$ node in layer.

$$O_{1i}=\mu_{A_i}(x) \qquad i = 1, 2 \qquad (1)$$

$$O_{1i}=\mu_{B_{i-2}}(y) \qquad i = 3, 4 \qquad (2)$$

where $\mu_{A_i}(x)$, $\mu_{B_{i-2}}(y)$ can adopt any fuzzy membership function. For example, if the triangular membership function is employed,

$$Triangle(x,a,b,c) = \begin{cases} 0, x \le a \\ \dfrac{x-a}{b-a}, a \le x \le b \\ \dfrac{c-x}{c-b}, b \le x \le c \\ 0, c \le x \end{cases} \qquad (3)$$

where parameters a, b and c decide the shape of triangular MF.

**Layer 2:** The nodes in this layer are labelled by $\pi$ Fig. 2. Each node in this layer satisfies the firing strength ($w_i$) of a rule. The firing strength may be the result of an AND or an OR operation, and it shapes the output function for the rule. In addition, it is known as "degree of fulfilment". The outputs $O_{2i}$ of this layer are the multiplication of inputs, that is to say, the inputs are the corresponding degrees from layer 1.

$$O_{2i}=w_i=\mu_{A}(x)\mu_{B_j}(y) \qquad i = 1, 2; j = 1, 2 \qquad (4)$$

**Layer 3:** The nodes in this layer are labelled with N to indicate that performs a normalization of the firing strength from previous layer. The outputs of this layer are named as "normalized firing strength". The output of each node in this layer is given by:

$$O_{3i} = \overline{w}_i = \frac{w_i}{\sum_{k=1}^{4} w_k} \qquad i = 1,..., 4 \qquad (5)$$

**Layer 4:** The output of each node is simply the product of normalized firing strength and a first order polynomial:

$$O_{4i} = \overline{w}_i z_i \overline{w}_i(p_i x + q_i y + r_i) \qquad i = 1,..., 4 \qquad (6)$$

where $z_i$ is a linear function of input variables.

**Layer 5:** The single node in this layer is labelled Σ. Its total output of the summation of all input is:

$$Z = O_{5i} = \sum_{i=1}^{4} \overline{w}_i z_i = \frac{\sum_{i=1}^{4} w_i z_i}{\sum_{i=1}^{4} w_i} \qquad (7)$$

Optimizing the values of adaptive parameters is vital importance for the performance of the adaptive system. In this ANFIS architecture, there are two adaptive layers, namely the first layer and the fourth layer. Layer 1 has modifiable parameters related to the input MF. The parameters in this layer are called premise parameters or antecedent. Namely, it means the initial (or "if") part of a fuzzy rule. Layer 4 also has three modifiable parameters ($p_i$, $q_i$, $r_i$) connecting with the first-order polynomial. These parameters are called consequent or conclusion which means the final (or "then") part of a fuzzy rule.

The task of the training or learning algorithm for this structure is to tune all modifiable parameters to make the ANFIS output match to the training data. This network is trained based on supervised learning. Hence, our target is to train adaptive networks to be able to approximate unknown functions given by training data and then find the exact value of the above parameters.

## 3. Results and discussion

In this paper, the net modal peak gain model of GaInP QW LDs with respect to different number of QWs and different injection levels is implemented using ANFIS structure. Although there are various optical gain models presented with respect to different parameters in literature, this model is specifically selected in order to show that an efficient and dynamic optical gain model can be developed with minimum number of experimental data.

In the proposed model, the optimal number of epoch is found to be 45 for training. The number of membership functions for both input variables; current density and number of QWs are 6. The number of rule is 36. It is clear from Eq. (3) that the triangular MFs are specified by three parameters. Consequently, the ANFIS used here contains a total of 144 (108 + 36 = 144) fitting parameters of which 36 (6x3 + 6x3 = 36) are the premise parameters and 108 (36x3=108) are the consequent parameters.

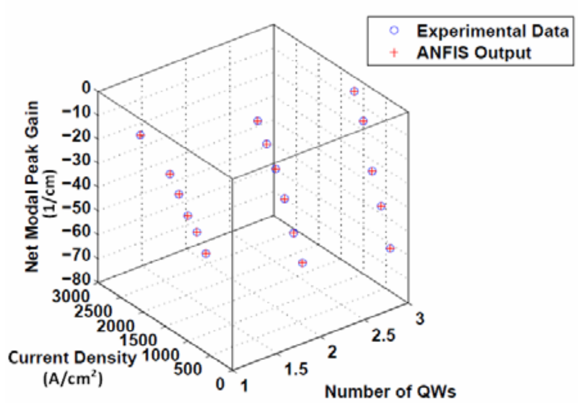


*Fig. 3. The comparison of the net modal peak gain and ANFIS results for GaInP multi-QW laser diode.*

The model is trained with the hybrid learning algorithm which shows the best results among other learning algorithms used in the analysis. The proposed approach successfully predicts the net modal peak gain values of GaInP QW LDs with respect to both different levels of current density and different number of QWs. In order to validate the proposed model, ANFIS results are compared with the experimental data [8] shown in Fig. 3. which are in very good agreement. Although the experimental data set is limited, the rms error for the hybrid algorithm is 3.15x 10-4 which supports the validity of the ANFIS model. In addition to that, the model tremendously reduces the computation time of which the training time takes only a few seconds after finding the most suitable network configuration and learning algorithm. Hence, the proposed model is very quick after being trained and does not require complicated mathematical functions with strong background knowledge.

This kind of similar models can be effectively used by optical design engineers for the purpose of quick simulations of the optical systems to evaluate the system performance.

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