

An accurate single CAD model based on radial basis function network

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A simple, single, new and an accurate CAD model is proposed for a type of semiconductor laser diode based on radial basis function network (RBFN). The single model easily computes the values of the critical quantities according to their operating wavelengths and injection currents which are differential modal gain, differential refractive index change and Alpha (α) parameter (linewidth enhancement factor, LEF). The computation time is tremendously reduced by the model and it can be used to evaluate the general system response at the design stage. The model results are considerably well-matched with the previously obtained experimental values.

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1. Introduction

CAD models are strongly required to evaluate the system performance at the design stage. These tools offer confidence by predicting interactions between the system components by simulation. Therefore, powerful and accurate CAD models are always required for optimizing different system designs. In this study, a quick and simple Quantum Cascade Laser (QCL) model is proposed which is recently invented and has been still developed, is a kind of semiconductor laser diodes [1]. QCLs emit light in the mid and far infrared portion of the spectrum and they are the most important light sources in the mid and far infrared wavelength range. They are used in environmental gas emission monitoring system and gas analyser for industrial emissions, process optimisation, trace level applications, metal detection, astronomical applications, and control of industrial plasma processes. Quantum cascade lasers have many advantages over other existing semiconductor lasers. They can operate in room temperature, a wide emission range, higher optical power tuning range and being small size [1].

The proposed single RBFN model offers the possibility of quick and accurate computation of the critical quantities of semiconductor lasers according to their injection currents and operating wavelengths which is shown in figure 1. The importance of the single model comes from the fact that it includes the characteristic quantities which are optical gain spectrum [2], refractive index change with injection current [3], and α parameter [4]. All these quantities are obtained after some lengthy mathematical calculations including strong background knowledge. The calculation procedures involve different theories, different approximations, assumptions and estimations. In addition to that the measurements of these quantities are difficult and requires numerous and expensive experimental optical setups. Since QCLs are fairly new technologies, an accurate single model of these

quantities is very important to obtain a simple model with a predictive capability for the characteristic quantities of QCLs.

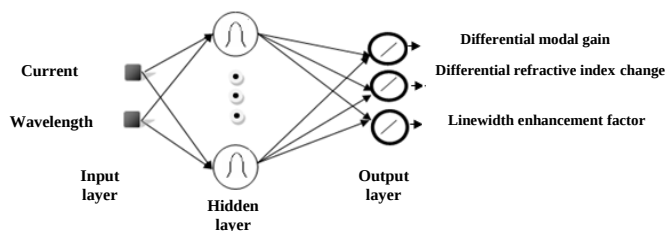


Fig. 1. RBFN model of QCL.

Artificial Neural Networks (ANNs) are widely used in many application domains [5]. ANNs are mostly used when problems are hard or impossible to solve by conventional algorithms. Some features they have such as ability to learn adaptively, fault tolerance, real time operation and generalization, make them powerful problem solving method. In this study, Radial Basis Function Networks which are universal approximators are used to develop a single efficient model for QCLs [6]. The training and the testing results show that the preferred ANN based method is efficient, simple and accurate. Additionally, the CAD model can reliably be used in systems that include QCLs to predict the response at the design stage.

2. Radial basis function network model

When a human brain and a digital computer are compared, the human brain possesses many advantages over a digital computer. The most fascinating aspect of the brain is the learning process. ANNs are considered as the simplified mathematical models of human brain. The computations of the brain are done by a highly

interconnected network of neurons. These neurons communicate by sending electric pulses through the neural wiring consisting of axons, synapses and dendrites [7]. Each processing element (neuron) has five components when it is considered as a mathematical model which is shown in Fig. 2. These components are inputs (x_i), weights (w_i), summing function (NET), activation function (f) and output (O). Data is presented at the input layer and weights represent the importance of information. Summing function computes NET of the processing element as follows:

$$NET = w_1x_1 + \dots + w_nx_n \quad (1)$$

Activation functions are necessary to introduce nonlinearity to the network. According to activation function the processing element output is given by the following formula:

$$O = f\left(\sum_{i=1}^n w_i x_i\right) \quad (2)$$

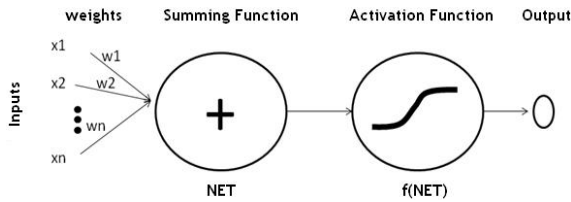


Fig. 2. Components of one neuron.

Radial basis function networks which can be used for function approximation are feed-forward networks. They are usually configured with one hidden layer which is composed of nonlinear units. Each hidden layer unit's basis function has the parameter center and width. The radial distance d_i is calculated by using Euclidean distance as follows:

$$d_i = \|u - c_i\| \quad (3)$$

where u is input vector and c_i is center vector of node i at hidden layer.

Output (h_i) of each hidden layer unit i is computed by applying basis function to this distance:

$$h_i = G(d_i, \sigma_i) \quad (4)$$

where σ_i is the i th variance.

Radial basis function is typically a Gaussian function which has a peak at zero distance from the node and

starting to decrease while distance from the center increases as shown Fig. 3. The transformation from the input unit to the hidden unit is nonlinear. However the transformation from the hidden unit to the output unit is linear [5]. Finally f^{th} output is computed as:

$$x_j = f_j(u) = w_{0j} + \sum_{i=1}^I w_{ij} h_i, \text{ where } j = 1, 2, \dots, M \quad (5)$$

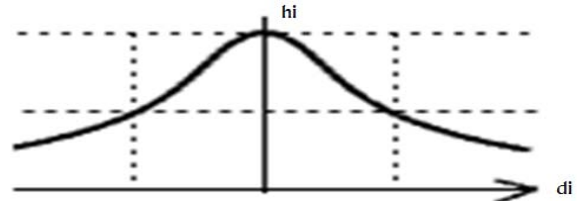


Fig. 3. Radial basis function.

In order to implement the model, a radial basis network is iteratively created with one neuron in hidden layer at a time. Neurons are added to the network until a maximum number of neurons have been reached or the sum-squared error falls beneath an error goal. The structure of RBFN model used in this study is showed in figure 1. As shown in the figure, three important QCL quantities are computed once at a time according to the input values of injection currents and operating wavelengths.

In this study, the experimental data that belongs to QCL lasers is used to develop a single CAD model in order to compute the characteristic quantities of QCLs [8]. The experimental data is divided in to two distinct set. By means of training, supervised learning is used so training set is presented as input to the network, while output of the corresponding input is known. After training, testing is performed to evaluate power of the single CAD model. The mean squared error (mse) is used for both training and testing phases to evaluate accuracy of results.

3. Results and conclusions

Besides center, RBF has also a radius (called a SPREAD) which is an extremely important constant for radial basis layer [9]. This determines the width of an area in the input space to which each neuron responds. SPREAD should be large enough that neurons respond strongly to overlapping regions of the input space. Since there is no method to learn the proper value of SPREAD constant, its value is tried in an interval to make sure that minimum mse error is achieved. SPREAD value is tried with 0.01 increments in the single CAD model. When this constant is equal to 0.3, minimum total test mse error is reached from the single model which is shown in Table 1. The results obtained from the RBFN CAD model are in good agreement with the experimental values of differential modal gain, differential refractive index

change and linewidth enhancement factor which is shown in Figs. 4-6, respectively.

Table 1. Optimal testing and training results of the single RBFN model.

SPREAD	0.3
Total Train mse	7.3250e-32
Total Test mse	0.0043

It is clearly seen that the single model results in terms of the test and the training, supports the validity and robustness of the model despite the fact that experimental data set is limited. The real-time calculation is in the order of microseconds. Therefore RBFN model is very fast after being trained and it requires no complicated mathematical functions. These models can be implemented in a personal computer for the estimation of these characteristic quantities without possessing any background knowledge of QCLs. Additionally, they can be useful for process engineers to evaluate the system response at the instant of designing the whole system.

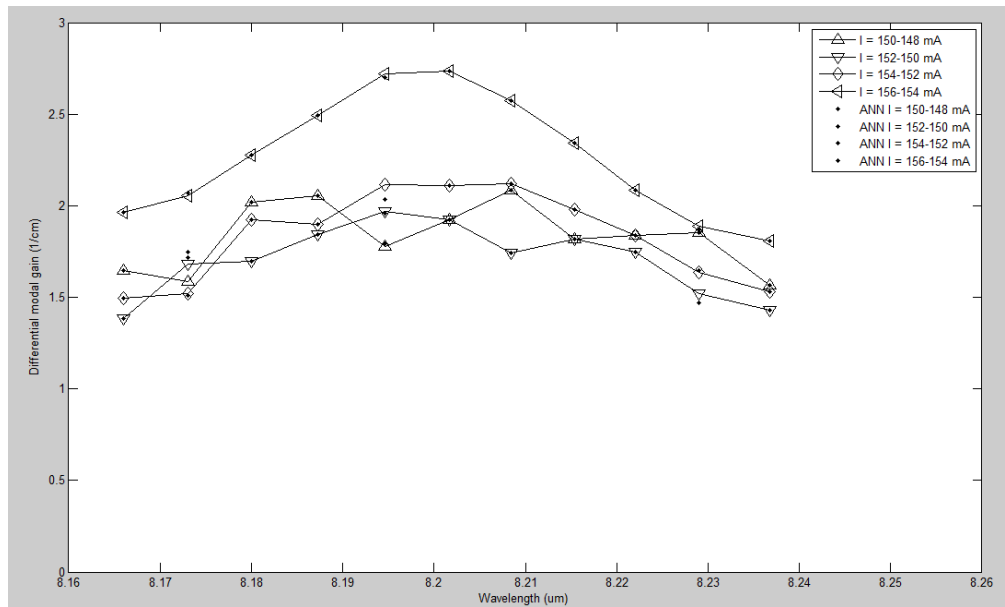


Fig. 4. Comparison of experimental and ANN RBFN single model results for differential modal gain.

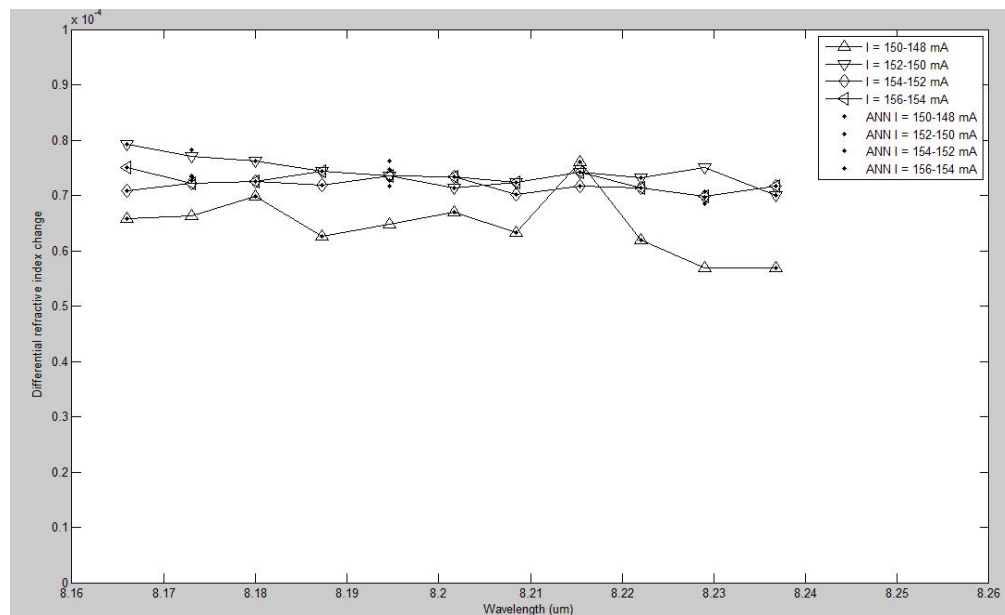


Fig. 5. Comparison of experimental and ANN RBFN single model results for differential refractive index change.

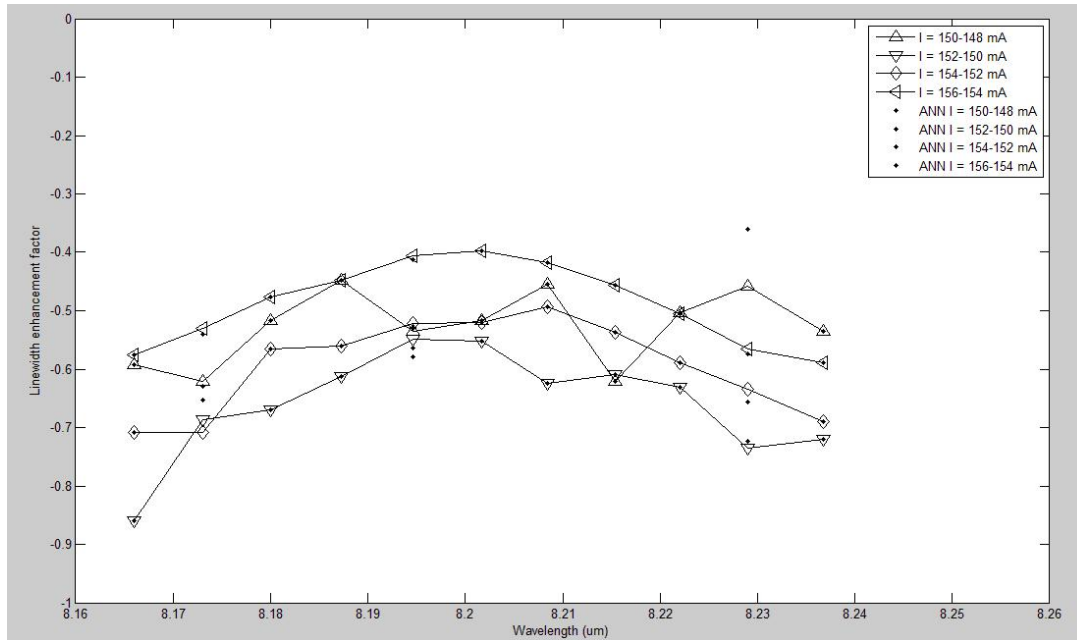


Fig. 6. Comparison of experimental and ANN RBFN single model results for the linewidth enhancement factor.

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