Optical gain model proposed with the use of artificial neural networks optimised by artificial bee colony algorithm

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This study presents a simple and accurate optical gain model for a quantum-cascade laser (QCL) based on artificial neural networks (ANNs). The training process is performed with Artificial Bee Colony (ABC) optimisation algorithm which enables highly accurate results for the proposed optical gain model. The results are in very good harmony with the previously obtained experimental gain model.

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Keywords: Artificial bee colony, Artificial neural network, Modelling, Optimisation, Optical gain, Laser diodes

1. Introduction

For any optical system, Computer aided design (CAD) models are strongly needed to evaluate the system performance at the design stage [1-16] since the realization of an optical system requires many high-cost experimental setups. In addition to that, there are many parameters that have to be accurately adjusted in order to match the CAD model during the design process of these systems.

Semiconductor laser diodes are necessary and indispensable elements of optoelectronic and photonic systems. QCL is a kind of semiconductor laser that emits in the mid-infrared region of the electromagnetic spectrum. They have many advantages over existing semiconductor lasers in terms of high power conversion efficiency, smaller in dimension, excellent reliability, and operable around room temperatures [17].

Optical gain is one of the most important characteristic quantities of semiconductor lasers which is also called modal gain that includes important knowledge about the evaluation and operating characteristics of the laser diodes [18]. To figure out the optical gain spectrum exactly, it is crucial to obtain a dynamic and an accurate gain model with predictive capability for QCLs since they represent a fundamentally new class of semiconductor lasers. Optical gain requires lengthy and complicated mathematical calculations using different theories and assumptions. In literature, there are a great deal of methods that have some advantages and disadvantages to acquire an accurate optical gain spectrum [19]. However, more reliable theoretical models and measurement techniques are still needed.

ANN is one of the data processing systems, which try to simulate features of the human brain and its learning process [20]. It is inspired by the way of biological nervous systems. The power of neural network comes from their ability to learn from experience, parallel processing, self organization, adaptability, fault tolerance and real-time operation properties [20]. So, they are widely used by researchers to solve different problems in optimization, classification, function approximation, and pattern recognition, etc. [21-24].

ABC algorithm which simulates intelligent foraging behaviour of honeybee swarms is proposed by Karaboğa et al. [25]. ABC is developed based on observing the behaviours of real honeybees on finding nectar-rich food sources and sharing the information of food sources to the bees in the hive. It is new, very simple, and robust population based optimization algorithm.

In recent years, there are successfully developed accurate and single models for optical gain [26,27] and other characteristic quantities of semiconductor laser diodes [28-30] by using different optimisation algorithms for the purpose of quick simulations. In this study, a new optical gain model for QCLs based on ANNs is proposed which is trained by the ABC algorithm. The model is based on the experimental data [31] that is obtained from amplified spontaneous emission spectroscopy. The model shows very good agreement in terms of both the training and the test results. The proposed model is constructed by using multi-layer perceptrons (MLPs) to model the relationship between the two inputs (current, wavelength) and one output (differential modal gain) which is shown Fig. 1.

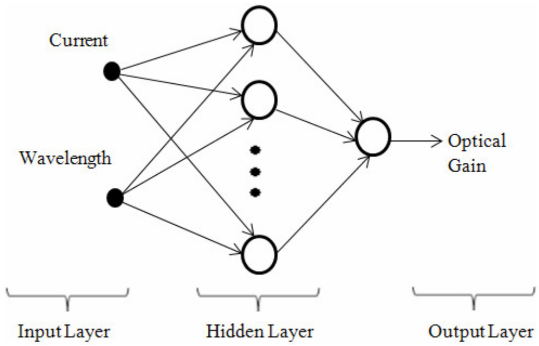

Fig. 1. The proposed gain model for QCLs.

2. ANN modelling

ANNs are powerful non-linear mathematical data modelling tools. They are especially used to identify and learn relationships between inputs and outputs in order to find correlated patterns in a data set. After training process, ANN predicts the outcome of new unknown input data, shortly it learns from examples.

An ANN is a parallel computational structure which consists of interconnected computational units called neurons. In terms mathematical modelling, each neuron has five basis components:

- *Inputs:* forward knowledge from environment to a neuron.
- *Weights:* coefficients that determine the affect of inputs on the neuron.
- *Summing Function:* computes net input multiplying by weights.
- *Activation Function:* processes the net input and computes the response based on the input (f(NET)).
- *Outputs:* forward the output to the environment or any other neuron.

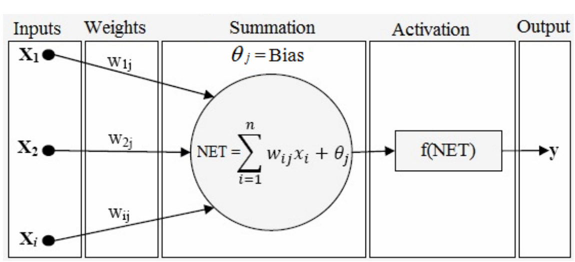

Fig. 2. The architecture of an artificial neuron.

Input passes through input layer with no chances. In the hidden layer, the information from each neuron of input layer x_i is multiplied by its weight w_{ij}. The weighted result is added to produce NET. After that the weighted sum NET is sent to an activation function which provides nonlinearity of neural network.

The training process is to find the correct values for the weights between inputs and outputs. Weights of the artificial neuron are adjusted by an optimisation algorithm. In the proposed study, ABC algorithm is used for training the experimental values.

In the ABC algorithm, the colony of artificial bees consists of three groups of bees: employed bees, onlookers and scouts. The position of a food source represents a possible solution to the optimization problem and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution. For every food source, there is only one employed bee. The number of the employed bees or the onlooker bees is equal to the number of solutions in the population. The employed bee whose food source has been exhausted by the bees becomes a scout [25].

Steps of ABC algorithm are as below:

1. Initialize food sources (possible solutions x_i, i=1,…, SN)
2. Evaluate the population
3. cycle = 1
4. repeat
   Produce new solutions v_i using (1) for employed bees and determine the quality of new solutions
   Apply the greedy selection process
   Calculate the probability values p_i of the food sources (x_i) by (2)
   Produce the new solutions v_i for the onlookers from the solutions x_i selected depending on p_i and evaluate them
   Apply the greedy selection process
   Complete the exploitation process of the sources
   Send the scouts to discover new food sources that is new randomly produced solutions
   Memorize the best solution found so far
   cycle = cycle+1
5. until cycle = MCN

An employed bee investigates near food sources in her memory to find more nectar-rich food sources and checks the nectar amount (fitness value) of the new source (new solution). This procedure is performed by producing a modification on the position (solution) in her memory ($\theta_i(c)$) depending on the local information.

$$\theta_i(c+1) = \theta_i(c) \pm \phi_i(c) \tag{1}$$

where $\phi_i(c)$ is randomly selected number between (-1,1) [32].

The nectar amount of the new one is higher than that of the previous one, the bee memorizes the new position and forgets the old one. Otherwise she keeps the position of the previous one in her memory [33].

After exploration process is completed, employed bees return to the hive and share their information about food sources with onlooker bees. An onlooker bee chooses a food source depending on the probability value (p_i) associated with nectar amount of that food source. This value is calculated by the following formula:

$$p_i = \frac{F(\theta_i)}{\sum_{k=1}^{SN} F(\theta_k)} \tag{2}$$

where $F(\theta_i)$ is nectar amount of food source in θ_i position.

In ABC algorithm, there are 3 substantial parameters to be specified:

1. *SN:* The number of food source positions (at the same time, this value is equal to the size of population).
2. *Limit value:* The number of trials for releasing a food source.
3. *MCN:* Maximum cycle number (Stopping criteria).

The proposed model is started with a random population with different seeds that represents the network weights. Training process continues until the mean square error (MSE) between all measured and calculated (ANN) values falls below a given threshold or maximum epoch number is reached. Hyperbolic tangent sigmoid function is chosen as transfer function of the neurons in the hidden layer. Three phases (employed bee phase, onlooker bee phase, scout bee phase) of ABC algorithm is employed to find the optimal weight set.

3. Results and conclusions

In the proposed optical gain model, optimisation process is successfully performed with ABC algorithm for the first time. Both the training and the test results are in very good agreement with the experimental values which indicates that the model can be included in the CAD design of optoelectronic and photonic systems without any hesitation.

For the optimal model, the ANN is in 2×10×1 structure which means that the network have 2 inputs (current, wavelength), 1 output (differential modal gain) and there are 10 neurons in the hidden layer. From engineering point of view, this is the optimal number of neurons which has the advantage of not being a complex architecture. Another advantage of the model is the computation time which is in the order of microseconds after finding the most suitable architecture. The data set is separated into 73% train and 27% test data. Parameters of ABC is selected in the way that, colony size is 2*SN which is 40. The value of limit is SN*D where D is the dimension of the problem. The maximum cycle number is 50000. Mean square error of the outputs associated with inputs falls into 0.0023 for train and 0.013 for test data respectively which is shown in Figs. 3 and 4.

In future, it is hoped to develop a compact model for a QCL that includes all characteristic quantities with the ABC algorithm by indicating the advantages and disadvantages of the model.

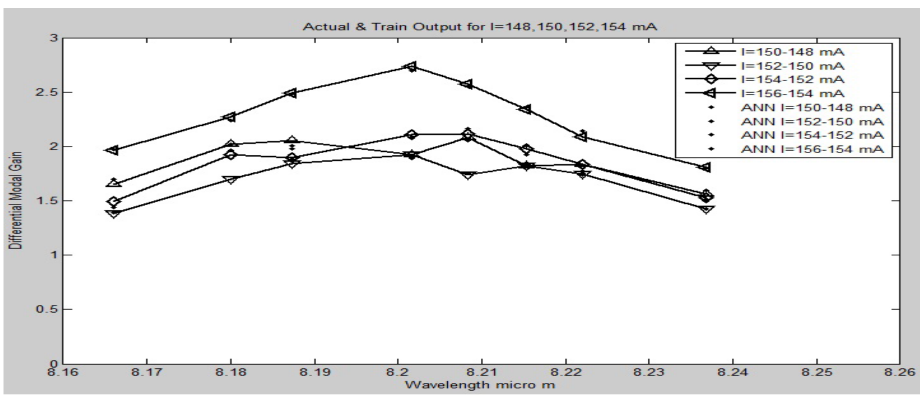

Fig. 3. Comparison of experimental and ANN model train results for differential modal gain.

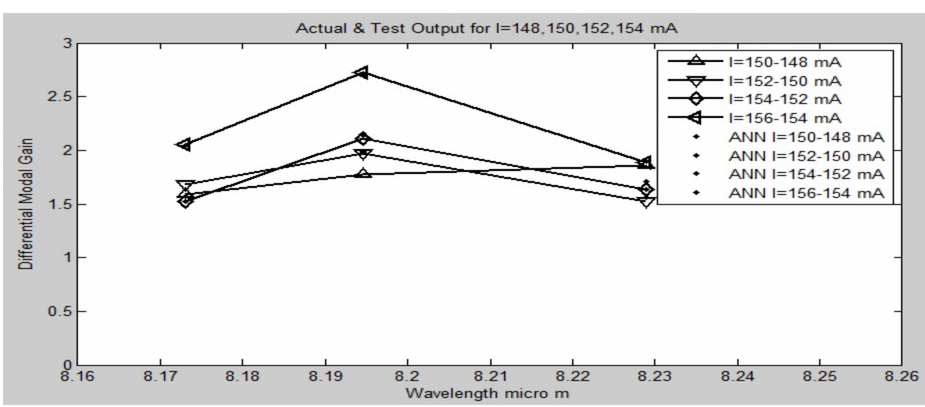

Fig. 4. Comparison of experimental and ANN model test results for differential modal gain.

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