A complete type II quantum cascade laser model with the use of RBFN

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Mid infrared quantum cascade lasers (QCLs) emitting in the 3-4 micron wavelength range have many potential applications in addition to sensitive gas detection since some gases have their strongest absorption features in this region. In this study, this type of QCL is intelligently modelled as a function of characteristic quantities (gain, refractive index change with injection current, linewidth enhancement factor) in terms of radial basis function network (RBFN). The single model results well matched with the experimental data reported elsewhere.

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1. Introduction

QCLs are unipolar devices that emit in the mid- to far-infrared portion of the electromagnetic spectrum and it is rapidly developed after its first demonstration [1]. In addition to different type of application areas, they are going to use as ultra-high sensitivity gas detection. Since many important hydrocarbon species and some other molecules (hydrogen halides) have their have their maximum absorption features in 3-4 micron wavelength range, their detection sensitivities are also maximised. This property enables many potential applications such as clinical diagnostics, outdoor and indoor pollution control systems, process monitoring and remote detection of oil and gas deposits and concealed weapon detection systems [2-4]. As a consequence, these areas strongly benefit from this technological breakthrough. Therefore, a strong motivation is needed for highly accurate computer aided design (CAD) based models to design high performance sensing systems in order to optimise many parameters.

The intelligent model consists of three inputs (characteristic quantities) which are differential gain, differential refractive index change with injection current and linewidth enhancement factor (LEF) [5-7]. Each quantity is obtained by lengthy and sophisticated mathematical calculations in addition to strong background knowledge. Understanding the gain spectra of a quantum cascade laser has crucial importance in order to develop a predictive capable model for the gain spectra. The refractive index change with injection current is also required for the characterization of QCLs which is similarly interrelated to the gain (Kramers-Kronig transformation), and robustly affects the distribution of inner cavity field. This change is mostly due to thermal heating as a consequence of current injection [8]. In addition to that, the measurement of the refractive index change with injection current is also difficult. The last quantity is the LEF which is strongly related to the QCL gain and enables information on the shape of gain. LEF is one of the key parameters for QCLs under both high-speed direct modulation and CW operation. The complexity is also well-known to measure the LEF as it dramatically changes with the operating wavelength, carrier density and other factors.

In recent decades, Artificial Neural Networks (ANNs) are beginning to be used as a computer aided design (CAD) approach in modelling simulation and optimisation as attractive and serious alternatives to traditional techniques [9]. They are information processing systems inspired by the ability of the human brain in order to learn from observations and to generalize it by an intelligent behaviour. ANN based CAD models are fast, accurate and reliable through some processes called training and testing phases. Learning process is intelligently achieved in the learning process and reliable predictions and generalizations are performed in the testing stage. ANNs have the ability to learn any arbitrary nonlinear input–output relationships from corresponding data by building an approximator. Multilayer Perceptron Networks and Radial Basis Function Networks are the most commonly used feedforward ANNs as approximators [10]. These are widely used for function approximation, pattern classification and recognition because of their structural simplicity.

QCL which belongs to type I has been previously modelled by using RBFN [11]. In this study, a candidate type II QCL for gas detection is modelled in terms of its characteristic quantities for different injection current and wavelength levels by using RBFN which is shown in Fig. 1. The single model results provide highly accurate results for each characteristic quantity based on the experimental results which has been previously published [12].

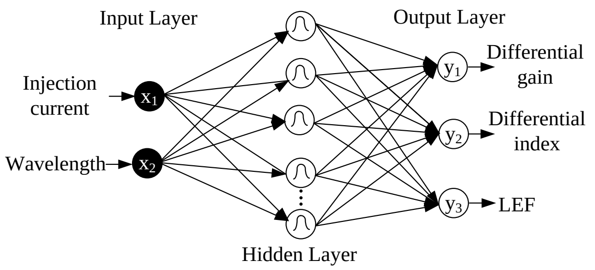

Fig. 1. RBFN model of type II QCL.

2. The proposed RBFN based model

RBFN is one of the commonly used special types of ANN feed-forward networks trained using a supervised training algorithm that uses a radial basis function as its activation function. They are frequently used for function approximation, curve fitting, time series prediction, and *classification* problems. RBFN offers several distinctive features due to their universal approximation, compact topology and faster learning speed. Due to these fascinating features, they have attracted considerable attention and they have been widely applied in many science and engineering fields [13-17].

To determine the optimal number of single hidden layer neurons is crucially important due to the network complexity and the generalization capability. In the case of insufficiency, the learning process cannot be achieved adequately. Conversely, it leads to weaken the generalization capability or overtraining (memorize instead of learning) although the error levels are considerably low [18]. Another factor is the position of the centres in the hidden layer which affects the network performance considerably [19]. In the hidden layer each neuron uses the Gaussian function which is the most favourite activation function. Afterwards, the optimization the SPREAD (RBF radius) parameter is achieved in the hidden layer [11]. Finally, the adjustments of the weights between the hidden layer and the output layer are performed in addition to the usage of linear activation function. The procedure is completed by adding the bias values to each output if necessary.

The analytical details of the RBFN modelling are given in the article for type I QCL laser [11]. The model implementation starts with one neuron in hidden layer at a time by the iterative creation of a radial basis network. 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 Fig. 1. As shown in the figure, three important type II QCL quantities are computed one at a time according to the different input values of injection currents and operating wavelengths.

3. Results and conclusions

The RBFN model is obtained for two different cases. In the first case, test phase is avoided because of the limited experimental data set which can be seen as a disadvantage. In this model the results are perfectly matched with the experimental data which indicates absolutely zero mean square error (MSE). In order to achieve a more realistic model second case is applied for four training data and the remaining three are left for the testing of the model. The graphs shown between Figs. 2-4 indicates the second case for each characteristic quantity that presents the comparison of the RBFN model with the experimental values

To illustrate the capability and flexibility of the proposed type II QCL model, the results are compared with the experimental values that show good agreement with the experimental values. This indicates the validation of the RBFN based proposed model. In addition to that, the simulation results confirm that all the characteristic quantities are computed in the order of milliseconds with a Pentium IV processor running at 3 GHz. This time interval implies the significant reduction in the computation time which all the characteristic quantities are computed at the same time. This time interval can even be reduced more by using faster computer systems.

The SPREAD constant should be large enough that neurons strongly respond to overlapping regions of the input space. Since there is no method to achieve the proper value of it, its value is tried in an interval to make sure that minimum MSE error is achieved. The SPREAD value is tried with 0.01 increments in the single type II QCL model. The minimal number of hidden neurons in the model is also computed (for minimum MSE) in order to avoid complexity of the network and to prevent from overtraining. Table 1 presents the model results for the second case by giving the optimised parameter values for minimum MSE error.

Table 1. Optimal model results.

SPREAD	0.73
Total Train MSE	4.8960e-24
Total Test MSE	0.0037
Number of hidden layer	16

After obtaining the optimum RBFN architecture model, it is easy to compute the critical characteristic quantities at each operating point without requiring rigorous mathematics. The proposed model can be simulated by anyone with a personal computer for the estimation of these characteristic quantities without having any background knowledge of this kind of semiconductor lasers. The model results can also be extended to extrapolate more powerful designs at the whole spectrum for the quick simulation of such and similar systems.

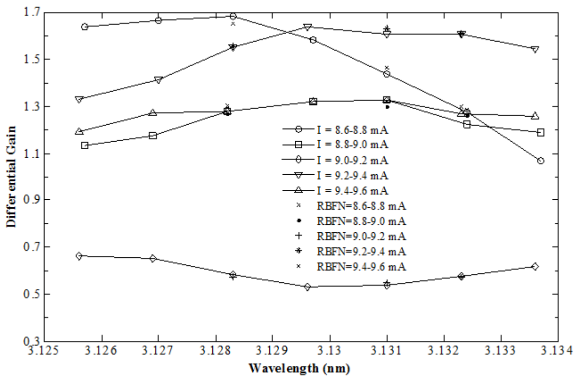

Fig. 2. Comparison of RBFN model with the experimental values for Differential Gain.

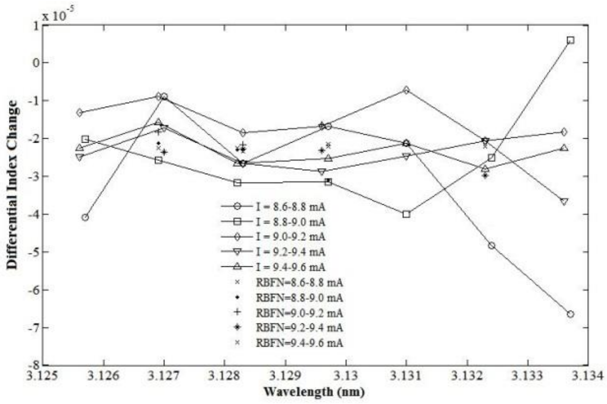

Fig. 3. Comparison of RBFN model with the experimental values for Differential Index Change.

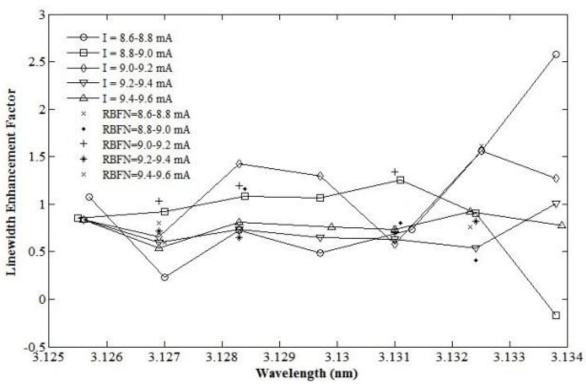

Fig. 4. Comparison of RBFN model with the experimental values for Linewidth Enhancement Factor.

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