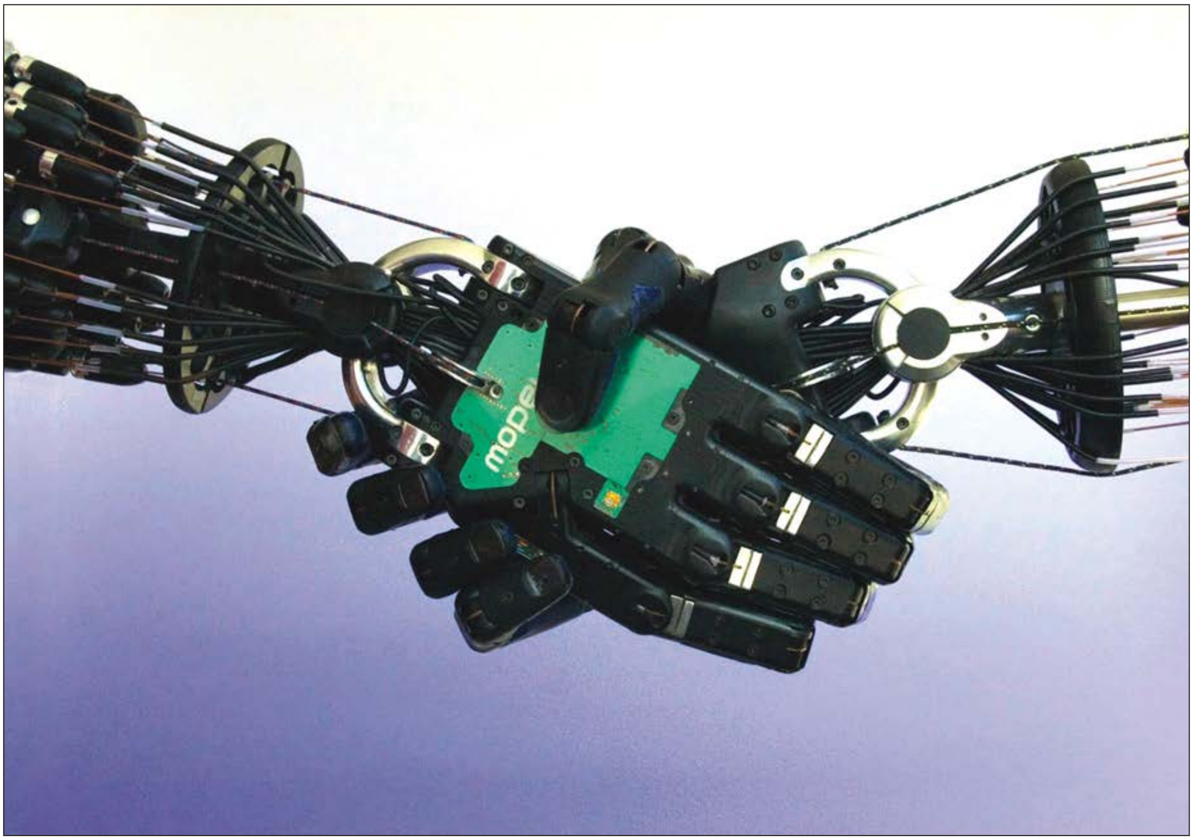

Journal of Artificial Intelligence

ISSN 1994-5450

Journal of Artificial Intelligence 5 (2): 76-84, 2012
ISSN 1994-5450 / DOI: 10.3923/jai.2012.76.84

A Complete CAD Model for Type-I Quantum Cascade Lasers with the use of Artificial Bee Colony Algorithm

Sevgi Yigit, Bulent Tugrul and Fatih Vehbi Celebi
Ankara University, Muh. Fak. Bilgisayar Muh. Bolumu Besevlar, Ankara, Turkey

Corresponding Author: Fatih Vehbi Celebi, Ankara University, Muh. Fak. Bilgisayar Muh. Bolumu Besevler, Ankara, Turkey

ABSTRACT

In this study, a simple and a single complete CAD model is obtained for type I quantum cascade laser based on characteristic quantities (optical gain, refractive index change, linewidth enhancement factor). The model is based on Artificial Neural Networks (ANNs) which is optimized by a new algorithm called Artificial Bee Colony (ABC). The developed model is capable of making fast and reliable predictions which is very useful in the CAD design of related systems. The inputs of the model are injection current and wavelength, respectively. The model agrees very well with the experimental findings that are previously published.

Key words: Quantum cascade laser, artificial bee colony algorithm, artificial neural networks, modeling, optical computing

INTRODUCTION

From each point of view, Computer Aided Design (CAD) models are recommended for each type of system since it at least involves brief information that how the system behaves under different operating conditions (Hsu and Peroulis, 2011; Xiao *et al.*, 2011; Cheng *et al.*, 2010; Schetzen *et al.*, 2008; Yildirim and Celebi, 2004; Gokrem *et al.*, 2010; Celebi and Yildirim, 2005; Yildirim and Celebi, 2009; Yucel *et al.*, 2011; Celebi, 2006; Yildirim and Celebi, 2010; Yildirim *et al.*, 2009; Danisman *et al.*, 2006; Ghoniemy *et al.*, 2004; Dagdeviren *et al.*, 2011). This is especially very important for the systems (optical) that have high cost experimental setups. In addition to that there are sometimes considerable amount of differences between theoretical and experimental values which are frequently encountered in optical related systems (Stohs *et al.*, 2001). Therefore, it is very important to develop intelligent and accurate CAD optical models to measure the performance of the system at the instant of design and simulation. The Quantum Cascade Lasers (QCLs) are novel devices that have wide range of applications where the power conversion efficiency is high (Faist *et al.*, 1994; Bai *et al.*, 2010). These applications are based on the tuning range where the emission changes from one wavelength (color) to another. This enables the usage of exact sensing of chemical vapors (carbon sulfide, carbon monoxide, nitrogen monoxide, carbonyl sulfide etc.), free space optical communications, infrared counter, metal detection and astronomical applications (Faist *et al.*, 1994). In addition to that, these semiconductor lasers are very small compared to other semiconductor lasers that produce light in the mid and far infrared portion of the spectrum which is not visible for human eyes. Therefore, accurate, dynamic and intelligent CAD models are needed for QCLs for the purpose of quick design and simulation according to different operating conditions of these systems. There are successfully implemented previous intelligent CAD models in optical area with the use of ANNs (Celebi *et al.*, 2006; Celebi, 2005a; Tankiz *et al.*, 2011; Celebi, 2010; Celebi, 2005b; Sagiroglu *et al.*, 2002; Celebi and Danisman, 2005; Celebi and Danisman, 2004, 2006) Fuzzy Logic (Yucel, 2011; Shen *et al.*, 2006; Celebi *et al.*, 2011) and hybrid (Neuro-fuzzy) (Yucel, 2011; Yuksel and Develi, 2005; Celebi and Altindag, 2009; Celebi *et al.*, 2009) systems which can be found in literature. These CAD models show intelligent behavior under different operating conditions and can be easily included in the design and simulation of sophisticated optical systems in order to get the proper response at the design stage. In our recent study, optical gain model for a QCL laser is developed by ANNs with the use of ABC algorithm (Yigit *et al.*, 2011). In this study, a complete and single model for a type I QCL is developed including refractive index change and linewidth enhancement factor in addition to the optical gain. The small error for each characteristic quantity from the single model shows that the model can be used in an optical system without any hesitation.

ARTIFICIAL NEURAL NETWORKS AND ABC ALGORITHM

Artificial Neural Networks (ANNs) are inspired by the ability of the brain to perform different operations and to process information (Haykin, 2000). They are learned from experience with no knowledge in advance. An ANN consists of large number of processing units called neurons. Each neuron has weighted inputs, summation function, activation function and an output. Neurons are stored in a nested layer structure. Each processing unit in each layer is connected to all processing units in the adjacent layers to form a network. The ANNs have fascinating features like: ability and adaptability to learn, generalizability, smaller information requirement, fast real-time operation and ease of implementation. Because of these features, there are so many studies implemented in the last few years (Khanale and Chitnis, 2011; Khanale, 2010; Salazar *et al.*, 2010; Bouzenada *et al.*, 2007; Soltani *et al.*, 2007; Dastorani *et al.*, 2010a; Dastorani *et al.*, 2010b; Anari *et al.*, 2011; Kumar, 2012; Mpallas *et al.*, 2011; Qasem and Shamsuddin, 2010; Hasheminia and Niaki, 2008).

Multi Layered Perceptrons (MLPs) are simplest and most commonly used neural network architectures. An MLP consists of three layers: an input layer, an output layer, one or more hidden layers (Danisman *et al.*, 2006). Input signals x_i generally passes through input layer with no change because of the linear activation function. The signals are carried along connections to each neuron in the hidden layer and amplified or inhibited through weights, w_i, associated with each connection. The nodes in the hidden layer act as summation devices for weighted signals (Minns and Hall, 1996). The incoming signal is transformed into an output signal, yi:

$$y_i = f\left(\sum w_{ij} x_i\right) \tag{1}$$

where, f is an activation function.

Training process is to produce known or desired output responses for the given input. The ANN is first initialized by assigning random numbers to the network weights. An input signal is then introduced to the input layer and the resulting output signal is compared to the desired output signal (Minns and Hall, 1996). The network weights are then adjusted by an optimization algorithm according to following equality:

$$w_{ji}(t+1) = w_{ji}(t) + \Delta w_{ji}(t+1) \tag{2}$$

During training, network weights are optimized until the error between ANN output and desired output falls below a specified level or maximum number of epochs is reached. Although the training is a time-consuming process, it can be done beforehand, offline. The trained neural network is then tested using new unseen data.

There are many types of neural networks for various applications in the literature. In this work, MLP is selected as the neural network architecture that is trained by ABC. ABC algorithm is inspired by natural bee colony and models their intelligent foraging behavior. The colony of artificial bees consists of three groups of bees: employed bees, onlookers and scouts. ABC algorithm is formed by three phases.

Pseudo-code of the ABC algorithm

```
Initialize food sources (possible solutions x_i, i = 1,..., SN)
Calculate the fitness values (f_i) of population
cycle = 1
repeat
    Produce new solutions v_i for employed bees and evaluate the fitness values (f_i) of new solutions
    Apply the greedy selection process
    Calculate the probability values p_i of the food sources (x_i)
    Produce the new solutions v_i for the onlookers from the solutions x_i selected depending on p_i and calculate the value f_i
    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
until cycle = MCN
```

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 (Karaboga and Basturk, 2007).

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 (θ_i (c)) depending on the local information:

$$\theta_i(c+1) = \theta_i(c) \pm \phi_i(c) \tag{3}$$

where, ϕ_i (c) is randomly selected number between (-1,1) (Karaboga and Akay, 2007).

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 (Karaboga and Basturk, 2007).

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:

$$p_i = \frac{F(\theta_i)}{\sum_{k=1}^{SN} F(\theta_k)} \tag{4}$$

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

The quality of a food source is determined by a specified fitness function. Mean Square Error (MSE) is selected as the fitness function in training MLP by the ABC algorithm. The mean square error is the mean value of the squared difference between the actual and the desired output of the ANN, for individual training patterns. The mean square error is defined as:

$$MSE = \frac{\sum (t_i - y_i)^2}{n} \tag{5}$$

where, t_i is the measured output, y_i is the predicted output value of the ANN.

Hyperbolic tangent sigmoid function is chosen as activation function of the neurons in the hidden layer.

ABC algorithm has three important parameters to be tuned and optimized:

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

RESULTS AND DISCUSSION

The proposed model involves training a MLP network by the ABC algorithm to compute the three characteristic quantities of QCL laser accurately in a single model that can be included in CAD design of related optical systems. Both the training and the test results are in very good agreement with the experimental values in literature (Kim *et al*., 2004).

The final ANN's structure is 2×30×3 which means that the network has 2 inputs (current, wavelength), 3 outputs (differential modal gain, differential refractive index change, linewidth enhancement factor) and there are 30 neurons in the hidden layer. The data set is split randomly into two parts: training set and testing set where the 73% of data is used as training and the remaining 27% of data is used as a testing set. 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 number of interconnection weights and biases in neurons. The maximum cycle number is 100000.

Training process is performed offline since it is time-consuming. After the optimal model is achieved, computation time of test process takes a few microseconds. Mean square error (the training and the test) for each characteristic quantity is given in Table 1 which shows very good agreement with the experimental values of the type-1 QCL data.

Table 1: MSE values for each QCL quantities

Parameter	MSE train data	MSE test data
Differential modal gain	0.0069	0.020
Differential refractive index change	3.6174e-012	2.6592e-012
Linewidth enhancement factor	0.0046	0.0045

In terms of the training and the test results, the detailed graphical results for each characteristic quantity is shown in Fig. 1 and 2 for differential modal gain, Fig. 3 and 4 for differential refractive index change and Fig. 5 and 6 for the linewidth enhancement factor,

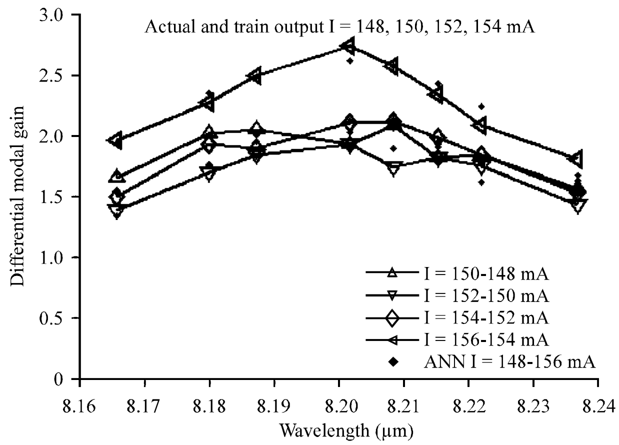

Fig. 1: Comparison of experimental and ANN model training results for differential modal gain

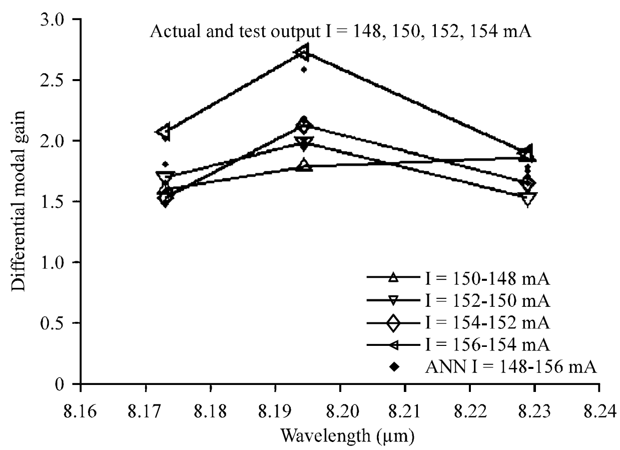

Fig. 2: Comparison of experimental and ANN model test results for differential modal gain

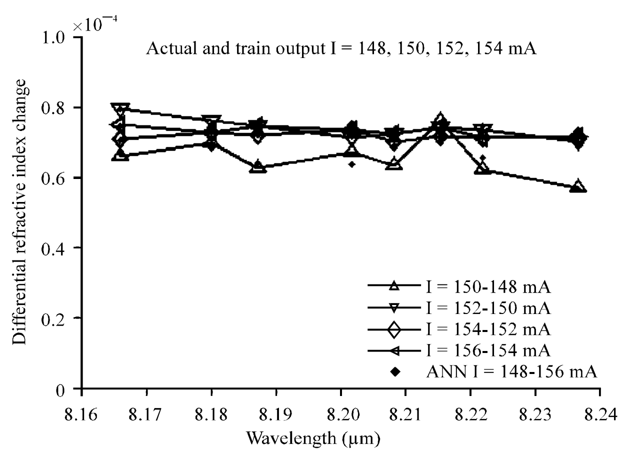

Fig. 3: Comparison of experimental and ANN model training results for differential refractive index change

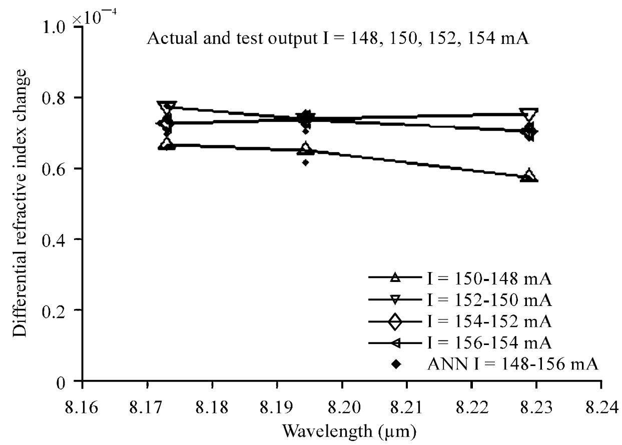

Fig. 4: Comparison of experimental and ANN model test results for differential refractive index change

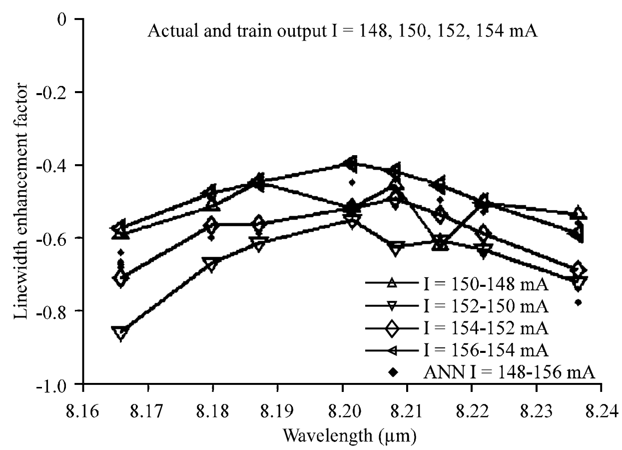

Fig. 5: Comparison of experimental and ANN model training results for linewidth enhancement factor

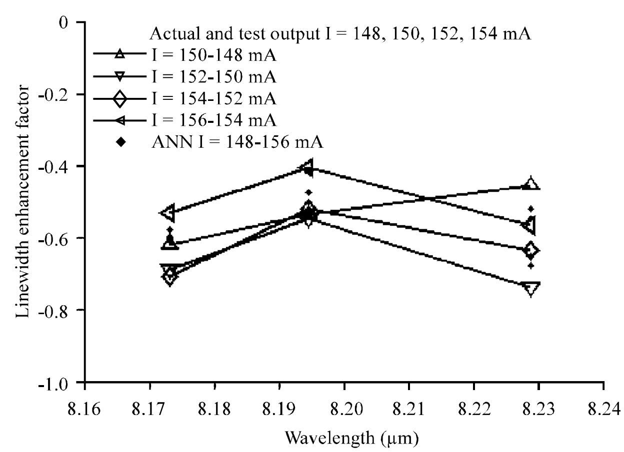

Fig. 6: Comparison of experimental and ANN model test results for linewidth enhancement factor

respectively. It is seen that, all graphs are also in very good agreement with the experimental values despite some small errors. In addition to that, experimental data set is limited which can be seen as a disadvantage.

One step forward of this study is to develop a compact single model that includes all types of QCLs optimized by using different artificial intelligence techniques.

REFERENCES

Anari, P.L., H.S. Darani and A.R. Nafarzadegan, 2011. Application of ANN and ANFIS models for estimating total infiltration rate in an arid rangeland ecosystem. Res. J. Environ. Sci., 5: 236-247.

Bai, Y., N. Bandyopadhyay, S. Tsao, E. Selcuk, S. Slivken and M. Razeghi, 2010. Highly temperature insensitive quantum cascade lasers. Applied Phys. Lett., Vol. 97, 10.1063/1.3529449

Bouzenada, M., M.C. Batouche and Z. Telli, 2007. Neural network for object tracking. Inform. Technol. J., 6: 526-533.

Celebi, F.V., 2005a. A different approach to gain computation in laser diodes with respect to different number of quantum-wells. Optik-Int. J. Light Electron Optics, 116: 375-378.

Celebi, F.V., 2005b. A proposed CAD model based on amplified spontaneous emission spectroscopy. J. Optoelectronics Adv. Materials, 7: 1573-1579.

Celebi, F.V. and K. Danisman, 2004. A different approach for the computation of refractive index change in quantum-well diode lasers for different injection levels. Proc. SPIE Int. Soc. Optical Eng., 5662: 384-388.

Celebi, F.V. and K. Danisman, 2005. Neural estimator to determine alpha parameter in terms of quantum-well number. Optics Laser Technol., 37: 281-285.

Celebi, F.V. and R. Yildirim, 2005. Distortion system theory of the two tone small signal input laser diode. J. Faculty Eng. Archit. Gazi Uni., 20: 373-377.

Celebi, F.V. and K. Danisman, 2006. A multi-layer perseptron network model for a quantum-well laser Diode. Proceedings of the International Conference on Computing and Informatics, June 6-8, 2006, Kuala Lumpur, pp: 601-604.

Celebi, F.V., 2006. Modeling of the linewidth enhancement factors of the narrow and wide GaAs well semiconductor lasers. J. Faculty Eng. Archit. Gazi Uni., 21: 161-166.

Celebi, F.V., I. Dalkiran and K. Danisman, 2006. Injection level dependence of the gain, refractive index variation and alpha parameter in board-area ingaas deep quantum-well lasers. Optik Int. J. Light Electron Optics, 117: 511-515.

Celebi, F.V. and T. Altindag, 2009. An accurate optical gain model using adaptive neurofuzzy inference system. J. Optoelectronics Adv. Materials-Rapid Commun., 3: 975-977.

Celebi, F.V., T. Altindag, R. Yildirim and L. Gokrem, 2009. Semiconductor laser modeling with ANFIS. Proceedings of the International Conference on Application of Information and Communication Technologies, October 14-16, 2009, Baku, Azerbaijan.

Celebi, N., 2010. An accurate single CAD model based on radial basis function network. J. Optoelectronics Adv. Mat. Rapid Commun., 4: 498-501.

Celebi, F.V., M. Yucel and H.H. Goktas, 2011. Fuzzy logic based device to implement a single CAD model for a laser diode based on characteristic quantities. Optik-Int. J. Light Electron Optics, (In press).

Cheng, Q.S., J.W. Bandler, S. Koziel, M.H. Bakr and S. Ogurtsov, 2010. The state of the art of microwave CAD: EM-based optimization and modeling. Int. J. RF Microwave Comput. Aided Eng., 20: 475-491.

Dagdeviren, M., E. Eraslan and F.V. Celebi, 2011. An alternative work measurement method and its application to a manufacturing industry. J. Loss Prev. Process Ind., 24: 563-567.

Danisman K, I. Dalkiran and F.V. Celebi, 2006. Design of a high precision temperature measurement system based on artificial neural network for different thermocouple types. Measurement, 39: 695-700.

Dastorani, M.T., A. Talebi and M. Dastorani, 2010a. Using neural networks to predict runoff from ungauged catchments. Asian J. Applied Sci., 3: 399-410.

Dastorani, M.T., H. Afkhami, H. Sharifidarani and M. Dastorani, 2010b. Application of ANN and ANFIS models on dryland precipitation prediction (case study: Yazd in Central Iran). J. Applied Sci., 10: 2387-2394.

Faist, J., F. Capasso, D.L. Sivco, C. Sirtori, A.L. Hutchinson and A.Y. Cho, 1994. Quantum Cascade Laser. Science, 264: 553-556.

Ghoniemy, S., L. MacEachern and S. Mahmoud, 2004. Analytical expressions, modeling and simulations of intensity and frequency fluctuations in directly modulated semiconductor lasers. Opt. Eng., 43: 224-233.

Gokrem, L., F.V. Celebi and R. Yildirim, 2010. Asymmetric amplitude variation for four tone small signal input GaN HEMT at different temperatures. J. Faculty Eng. Archit. Gazi Uni., 25: 779-786.

Hasheminia, H. and S.T.A. Niaki, 2008. A hybrid method of neural networks and genetic algorithm in econometric modeling and analysis. J. Applied Sci., 8: 2825-2833.

Haykin, S., 2000. Neural Networks: A Comprehensive Foundation. Macmillan College Publishing Company, Boston, USA.

Hsu, H.H. and D. Peroulis, 2011. A CAD Model for Creep Behavior of RF-MEMS Varactors and Circuits. IEEE Trans. Microwave Theory Tech., 59: 1761-1768.

Karaboga, D. and B. Akay, 2007. Artificial bee colony algorithm (ABC) on training artificial neural networks. IEEE 15th Signal Process. Commun. Applic., 2: 1-4.

Karaboga, D. and B. Basturk, 2007. A powerful and efficient algorithm for numerical function optimization: Artificial Bee Colony (ABC) algorithm. J. Global Optimizat., 39: 459-471.

Khanale, P.B. and S.D. Chitnis, 2011. Handwritten devanagari character recognition using artificial neural network. J. Artificial Intell., 4: 55-62.

Khanale, P.B., 2010. Recognition of marathi numerals using artificial neural network. J. Artificial Intell., 3: 135-140.

Kim, J., M. Lerttamrab, S.L. Chuang, C. Gmachl, D.L. Sivco, F. Capasso and A.Y. Cho, 2004. Theoretical and experimental study of optical gain and linewidth enhancement factor of type-I Quantum-Cascade Lasers. IEEE J. Quantum Electron., 40: 1663-1674.

Kumar, A.V.S., 2012. Diagnosis of heart disease using fuzzy resolution mechanism. J. Artif. Intell., 5: 47-55.

Minns, A.W. and M.J. Hall, 1996. Artificial neural networks as rainfall-runoff models. J. Sci. Hydrol., 41: 399-417.

Mpallas, L., C. Tzimopoulos and C. Evangelides, 2011. Comparison between neural networks and adaptive neuro-fuzzy inference system in modeling lake kerkini water level fluctuation lake management using artificial intelligence. J. Environ. Sci. Technol., 4: 366-376.

Qasem, S.N. and S.M. Shamsuddin, 2010. Generalization improvement of radial basis function network based on multi-objective particle swarm optimization. J. Artif. Intell., 3: 1-16.

Sagiroglu, S., F.V. Celebi and K. Danisman, 2002. Modelling of the linewidth enhancement factor with the use of radial basis function network. Int. J. Elect. Commun., 56: 51-54.

Salazar, R., U. Schmidt, C. Huber, A. Rojano and I. Lopez, 2010. Neural networks models for temperature and CO_2 control. Int. J. Agric. Res., 5: 191-200.

Schetzen, M., R. Yildirim and F.V. Celebi, 2008. Intermodulation distortion of the single-mode laser-diode. Applied Phys. B Lasers Opt., 93: 837-847.

Shen, H., Y.J. Shi, Z.Q. Yao and J. Hu, 2006. Fuzzy logic model for bending angle in laser forming. Materials Sci. Technol., 22: 981-986.

Soltani, S., H. Babaei, K.A. Zeynali and A. Jouyban, 2007. Modelling vasorelaxant activity of some drugs/drug candidates using artificial neural networks. J. Pharmacol. Toxicol., 2: 411-426.

Stohs, J., D.J. Bossert and D.J. Gallant, 2001. Gain, refractive index change and linewidth enhancement factor in broad-area GaAs and InGaAs quantum-well lasers. IEEE J. Quantum Electron., 37: 1449-1459.

Tankiz, S., F.V. Celebi and R. Yildirim, 2011. Computer-aided design model for a quantum-cascade laser. IET Circuits, Devices Syst., 5: 143-147.

Xiao, D., H. Lin, C. Xian and S. Gao, 2011. CAD mesh model segmentation by clustering. Comput. Graphics, 35: 685-691.

Yigit, S., R. Eryigit and F.V. Celebi, 2011. Optical gain model proposed with the use of artificial neural networks optimised by artificial bee colony algorithm. J. Optoelectron. Adv. Mat. Rapid Commun., 5: 1026-1029.

Yildirim, R. and F.V. Celebi, 2004. Design of a chaotic optical communication system by using RAMAN with noise addition technique. Proc. SPIE, 5662: 389-394.

Yildirim, R. and F.V. Celebi, 2009. The computation of the angle between the gain and photon population by geometrical approach. J. Faculty Eng. Archit. Gazi Uni., 24: 709-714.

Yildirim, R., H.G. Yavuzcan, F.V. Celebi and L. Gokrem, 2009. Temperature dependent Rolletti stability analysis of GaN HEMT. Optoelectronics Adv. Mat. Rapid Commun., 3: 781-786.

Yildirim, R. and F.V. Celebi, 2010. Harmonic amplitude control in laser diodes with non-linear feedback. J. Faculty Eng. Archit. Gazi Uni., 25: 163-170.

Yucel, M., 2011. Fuzzy logic-based automatic gain controller for EDFA. Microwave Optical Technol. Lett., 53: 2703-2705.

Yucel, M., H.H. Goktas and F.V. Celebi, 2011. Temperature independent length optimization of L-band EDFAs providing flat gain. Optik-Int. J. Light Electron Opt., 122: 872-876.

Yuksel, M.E. and I. Develi, 2005. A neuro-fuzzy computing technique for modeling the laser diode nonlinearity in radio-over-fibre link. Int. J. RF Micr. Comp. Aided Eng., 15: 329-335.