Intelligent modelling of alpha (α) parameter; comparison of ANN and ANFIS cases

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In this study, intelligent models are proposed for the Alpha (α) parameter or so called linewidth enhancement factor (LEF) which is an important parameter influencing many static, dynamic and noise characteristics of semiconductor lasers. The models are obtained with the use of artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) approaches. The proposed approaches are in very good agreement with the previously published experimental values.

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1. Introduction

In the last decade, intelligent models [1-33] are started to use for system design and simulation in addition to the developed theoretical models [34-58] in semiconductor lasers, optics and optical materials. These intelligent models are useful flexible tools for the quick design and simulation of such systems and they are efficient alternatives to conventional methods which can be computationally expensive. From analytical point of view, it can be difficult to obtain for empirical models whose range and accuracy can also be limited.

α parameter or LEF is an important design parameter for semiconductor lasers and it is defined as the ratio of carrier-induced variation of real and imaginary parts of the material's susceptibility [59]. It is one of the main features that distinguish the behaviour from other types of lasers. It determines several fundamental aspects like linewidth, chirp, mode stability, laser dynamics, and behaviour in presence of optical feedback, and the occurrence of filamentation [60-61].

There are several methods proposed for both the calculation and the measurement of this non-linear parameter under different assumptions, different approximations and different operating conditions [62-71]. In this study, two intelligent models for α parameter of a distributed feedback (DFB) laser is proposed based on ANN and ANFIS modelling techniques. The experimental data belongs to a DFB laser which is previously published that includes all experimental details [72]. The overall results are compared including the theoretical case which also appears in the same article. Both intelligent models are accurate however ANFIS based one is more accurate compared to the ANN model under the same test vectors for the quick computation of α parameter.

2. ANN and ANFIS models proposed for α Parameter

ANNs are intelligent computing techniques based on the biological neuron processing which detects the patterns and relationships in data by training through experience. Neurons are connected with weights that create the power of ANNs which is useful in the modelling of nonlinear cases. The behaviour of these systems is settled by the activation functions of the processing elements, learning rule and network architecture. The weights of the neurons are adjusted during the training process to achieve the desired input-output relationship of the supervised network. This process goes on until the error is minimised and the network accomplishes the predefined level of accuracy with the use of a learning algorithm. The learning algorithm gives the weight change of a connection between neurons i and j at time t. After the successful completion of the training, the testing process begins which the unused information is given as inputs of the network that evaluates the test results. The specified technique is very useful in nonlinear relationship data that are frequently faced in engineering like in α parameter. The detailed knowledge about ANNs can be found in [73-77].

ANFIS is also an effective method developed by Dr. Roger Jang which places an important role in the modelling of nonlinear systems. These systems are fuzzy systems which use artificial neural networks theory in order to determine their properties (fuzzy sets and fuzzy rules) by processing data sets [8, 78-81]. In the ANFIS, the membership function parameters are extracted from a data set that describes the system behaviour. The ANFIS learns features in the data set and adjusts the system parameters according to a given error criterion [76, 80]. Using a predetermined input/output data set, ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are adjusted using either a back propagation learning algorithm alone, or in combination with a least squares type (hybrid) of method. This allows your fuzzy systems to model the used data. This approach is used in many system identification techniques that hypothesizing a parameterized model structure which relate input to membership functions (MFs) to rules to outputs to membership functions, and so on. After obtaining the useful input/output data for training, ANFIS is used to train the FIS model to emulate the data presented to it by tuning the membership function parameters according to a predetermined error criterion. If the training data cannot fully represent of all the features that are presented to the input of the model, then there is a need for the model validation. The input vectors from input/output data sets on which the FIS is not trained, are inputted to the trained FIS model to evaluate how well the FIS model predicts the corresponding data set output values. This method is also useful for the modelling of α parameter which has a strong nonlinear dependence. The details of the ANFIS method can be found in [79-81].

There are different ANN architectures and structures used in literature and in this study multilayer perceptron (MLP) network structure is used which is one of the most commonly used well-known universal approximators for system identification [82, 83]. The MLP ANN model used in this study is given in Fig. 1 which has 2 inputs named injection current and wavelength and 1 output named α parameter. For the ANFIS case the inputs and the output are the same and its structure is given in Fig. 2.

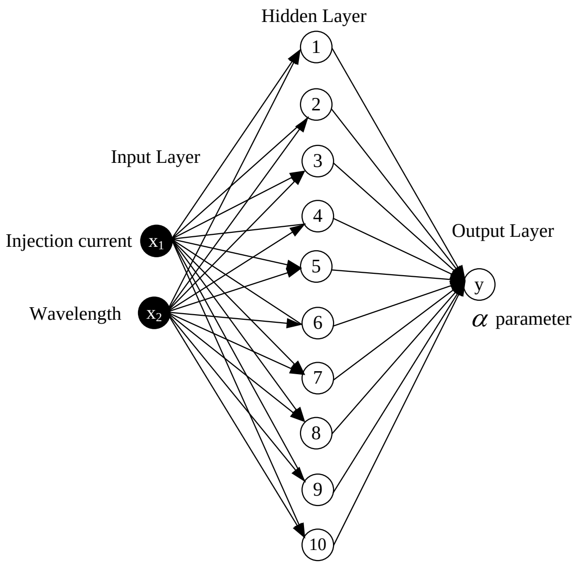

Fig. 1. Structure of the MLP ANN model for α parameter computation.

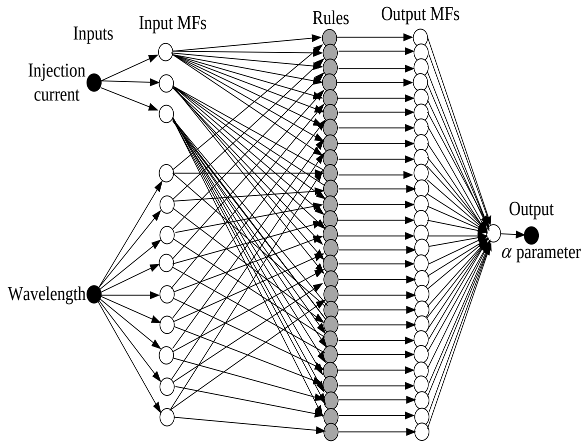

Fig. 2. Structure of the multiple input single output ANFIS model for α parameter computation.

3. Results and Conclusions

In this study, the intelligent modelling of α parameter for a DFB laser diode is performed successfully which is useful for the quick design and simulation of optical and laser related systems. Both ANFIS and ANN model results are very close to experimental values that validates the model results in both cases.

In ANFIS case, Sugeno-type FIS is used in the modelling process by using grid partition. In addition to that, triangular MFs are used for the fuzzification of input data that gives the best results. Hybrid learning updates the parameters of adaptive neurons in each epoch to minimize the error [83]. Figs. 3 and 4 show the initial and final MFs of the injection current and wavelength inputs developing the ANFIS model by grid partition before and after the learning process, respectively. The distribution between MFs that gives optimum results is shown in the Figs. 3.b and 4.b. The ANFIS parameters used in the model is shown in Table 1.

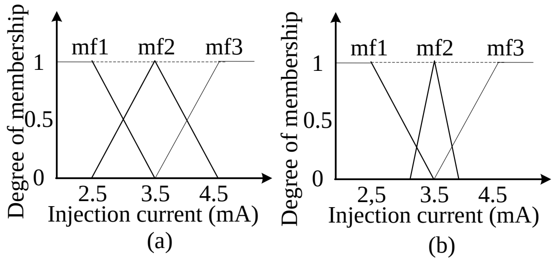

Fig. 3. (a) Membership functions before learning the injection current (b) Membership functions after learning the injection current.

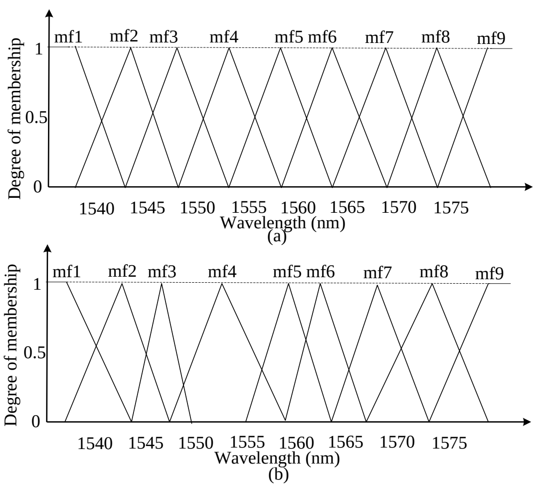

Fig. 4. (a) Membership functions before learning the wavelength (b) Membership functions after learning the wavelength.

Table 1. Information about the ANFIS.

Number of training vectors	42
Number of test vectors	17
Number of layer	5
Size of input data set	2
Number of output	1
Membership function	Triangle
Training algorithm	Hybrid
Learning rules	27
Number of epoch	500

For the MLP ANN model case, the optimum model is obtained within the 2 × 10 × 1 configuration that consists of a single hidden layer with 10 neurons in addition to the 2 inputs and 1 output with the hyperbolic tangent activation function. The model parameters are shown in Table 2.

Table 2. Information about the ANN.

Number of training vectors	42
Number of test vectors	17
Neurons of the input layer	2
Neurons of the hidden layer	10
Neurons of the output layer	1
Activation function of the network	Hyperbolic tangent
Training algorithm	Levenberg–Marquardt
Training epochs	45

Finally the comparison of all the results for different injection current levels is compared in Figs. 5.a, b, c respectively. Since the results obtained from both intelligent models are highly accurate, a comparison based on the errors are performed separately which is shown in Table 3. The correlation coefficient R is very close to unity for both cases. However error levels show that ANFIS results are more accurate compared to the ANN case in terms of all different error types under the same test vectors.

It can be concluded that ANFIS intelligent model for α parameter of a DFB laser diode is more useful and reliable compared to the ANN model and it can be used as a simple intelligent model for the design and simulation of such kind of systems.

Table 3. Table performance index to evaluate the prediction capability of ANFIS and ANN.

	ANFIS		ANN	
Parameters	Train	Test	Train	Test
MSE	0,000818	0,001393	0,140351	0,148195
RMSE	0,028600	0,037335	0,039690	0,041808
MAE	0,015745	0,028087	0,119443	0,145394
R	0,999795	0,999288	0,988713	0,984504

(MSE: Mean square error, RMSE: Root Mean square error, MAE: Mean absolute error, R: Correlation coefficient)

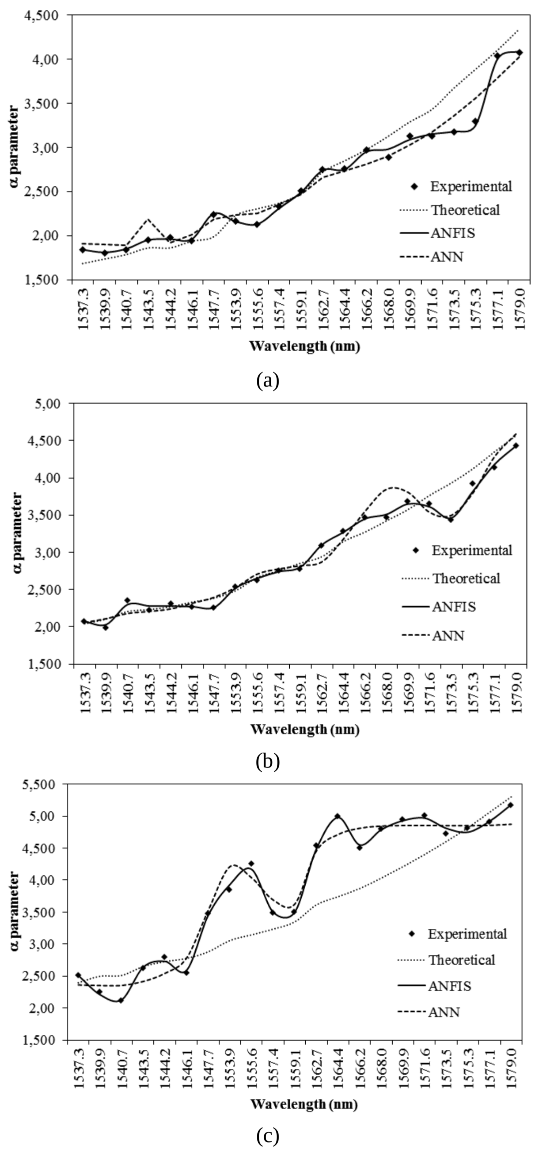

Fig. 5. Comparison of the all results for (a) 2.5 mA, (b) 3.5 mA, (c) 4.5 mA levels.

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