

Artificial neural network modeling studies to predict the yield of enzymatic synthesis of betulinic acid ester

Mansour Ghaffari Moghaddam

Faculty of Science
University Putra Malaysia
43400 UPM Serdang, Selangor, Malaysia
E-mail: mansghaffari@gmail.com

Faujan Bin H. Ahmad*

Faculty of Science
University Putra Malaysia
43400 UPM Serdang, Selangor, Malaysia
E-mail: faujan@fsas.upm.edu.my

Mahiran Basri

Faculty of Science
University Putra Malaysia
43400 UPM Serdang, Selangor, Malaysia

Mohd Basyaruddin Abdul Rahman

Faculty of Science
University Putra Malaysia
43400 UPM Serdang, Selangor, Malaysia

Financial support: This project was financed by a grant from RUGS (No. 9135500), Universiti Putra Malaysia, Malaysia.

Keywords: acylation, artificial neural network, betulinic acid, *Candida antarctica* lipase, enzymatic synthesis, Novozym 435.

Abbreviations: AAD: absolute average deviation
ANN: artificial neural network
BBP: batch backpropagation
GUI: graphical user interface
IBP: incremental backpropagation
LM: Levenberg-Marquardt
MLP: multi-layer perceptron
MSE: mean squared error
QP: quick propagation
R²: coefficient of determination
RMSE: root mean squared error

3 β -O-phthalic ester of betulinic acid was synthesized from reaction of betulinic acid and phthalic anhydride using lipase as biocatalyst. This ester has clinical potential as an anticancer agent. In this study, artificial neural network (ANN) analysis of *Candida antarctica* lipase (Novozym 435) -catalyzed esterification of betulinic acid with phthalic anhydride was carried out. A multilayer feed-forward neural network trained with an error back-propagation algorithm was incorporated for developing a predictive model. The input parameters of the model are reaction time, reaction temperature, enzyme amount and substrate molar ratio while the percentage isolated yield of ester is the output. Four different training algorithms, belonging to two classes, namely gradient descent and Levenberg-

Marquardt (LM), were used to train ANN. The paper makes a robust comparison of the performances of the above four algorithms employing standard statistical indices. The results showed that the quick propagation algorithm (QP) with 4-9-1 arrangement gave the best performances. The root mean squared error (RMSE), coefficient of determination (R²) and absolute average deviation (AAD) between the actual and predicted yields were determined as 0.0335, 0.9999 and 0.0647 for training set, 0.6279, 0.9961 and 1.4478 for testing set and 0.6626, 0.9488 and 1.0205 for validation set using quick propagation algorithm (QP).

Betulinic acid, 3 β -hydroxy-lup-20(29)-ene-28-oic acid (1) is a naturally occurring pentacyclic lupane-type triterpene.

*Corresponding author

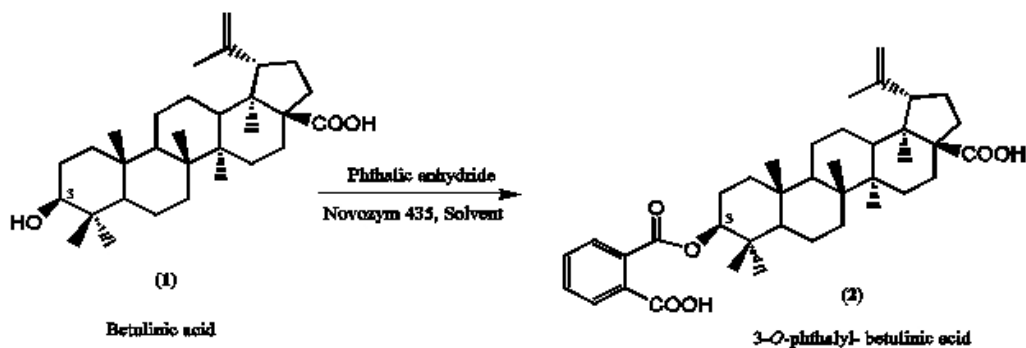


Figure 1. Reaction between betulinic acid and phthalic anhydride using Novozym 435 as biocatalyst.

It shows a broad range of biological and properties such as inhibition of human immunodeficiency virus (HIV), anti-bacterial, anti-malarial, anti-inflammatory, anthelmintic, antioxidant and anticancer properties (Yogeeswari and Sriram, 2005). However, the medical uses of betulinic acid in the pharmaceutical industry is strongly limited since it is insoluble in water (0.02 mg/mL), which causes a difficulty in preparation of injectable formulations for biological assays and decreases its bioavailability in the organism. The introduction of polar groups at the C-3 and C-28 positions such as phthalates, amino acids or sugar moieties, in certain cases, increases the hydrosolubility and anticancer activity (Thibeault et al. 2007; Gauthier et al. 2008).

The methods for the synthesis of 3-O-acyl-betulinic acid esters based on chemical catalytic esterification have been described (Mukherjee et al. 2004; Kvasnica et al. 2005; Mukherjee et al. 2006; Rajendran et al. 2008), which have a series of disadvantages (*e.g.* formation of many by-products and high energy consumption) (Yasin et al. 2008). In contrast, application of enzymes in organic synthesis provides advantages in comparison with conventional chemical methods such as mild reaction condition, high selectivity, high catalytic efficiency and high product purity and quality (Loughlin, 2000; Zarevuka and Wimmer, 2008).

Artificial neural network (ANN) is a highly simplified model of the structure of a biological network (Mandal et al. 2009). The fundamental processing element of ANN is an artificial neuron (or simply a neuron). A biological neuron receives inputs from other sources, combines them, performs generally a nonlinear operation on the result, and then outputs the final result (Bas and Boyaci, 2007). The basic advantage of ANN is that it does not need any mathematical model since an ANN learns from examples and recognizes patterns in a series of input and output data without any prior assumptions about their nature and interrelations (Mandal et al. 2009). ANN eliminates the limitations of the classical approaches by extracting the desired information using the input data. Applying ANN to

a system needs sufficient input and output data instead of a mathematical equation (Ali Akcayol and Cinar, 2005). ANN is a good alternative to conventional empirical modeling based on polynomial and linear regressions (Kose, 2008).

Recently, ANNs are the most popular artificial learning tool in biotechnology, with applications ranging from pattern recognition in chromatographic spectra and expression profiles, to functional analyses of genomic and proteomic sequences (Manohar and Divakar, 2005). Many applications of the ANN for prediction of the biotechnological processes have been reported in the literatures (Manohar and Divakar, 2005; Szaleniec et al. 2006; Bas et al. 2007; Silva et al. 2008; Abdul Rahman et al. 2009). For example, Manohar and Divakar (2005) reported an analysis of enzymatic esterification of anthranilic acid with methanol using artificial neural network. Methanol concentration, enzyme concentration, period of incubation, buffer volume and log P-values were input parameters, while the percentage yield of ester was the output. The optimized values of network for learning rate and momentum were 0.6 and 0.8, respectively. The learning was completed in 388 cycles with an average absolute deviation of 5.7%. For testing data, absolute deviation of predicted yield was varied between 1.3 and 33%. The average absolute deviation of the predicted values from experimental values was 15%. Abdul Rahman et al. (2009) have presented an artificial neural network (ANN) trained by backpropagation algorithm to predict the yield of enzymatic synthesis of dioctyl adipate. Reaction temperature, reaction time, amount of enzyme, and substrate molar ratio were the four input variables. The best network was found to be composed of seven hidden nodes using a hyperbolic tangent sigmoid transfer function. The correlation coefficient (R^2) and mean absolute error (MAE) values between the actual and predicted responses were 0.9998 and 0.0966 for the training dataset, and 0.9241 and 1.9439 for the validating dataset.

Employing neural network models would lead to saving time and cost by predicting the results of the reactions so

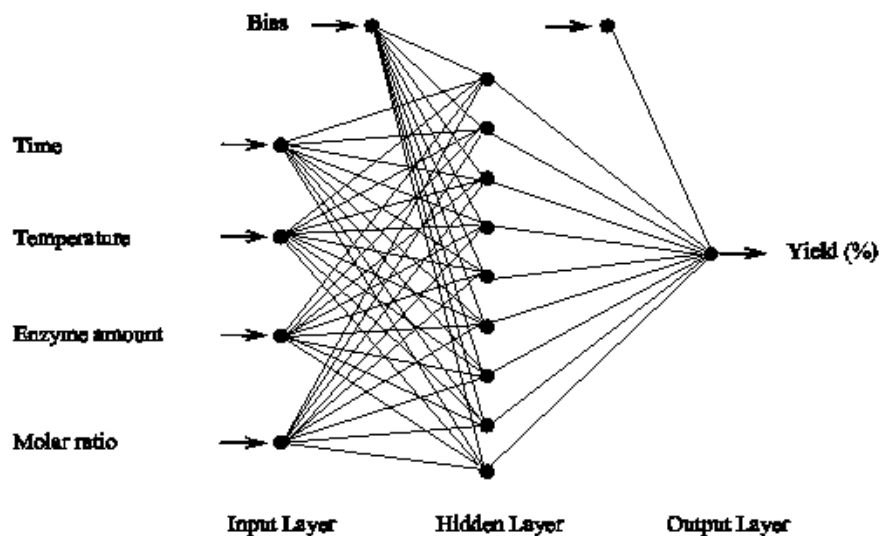


Figure 2. A multilayer feedforward perceptron (MLP) network consisting of four inputs, one hidden layer with nine neurons and one output.

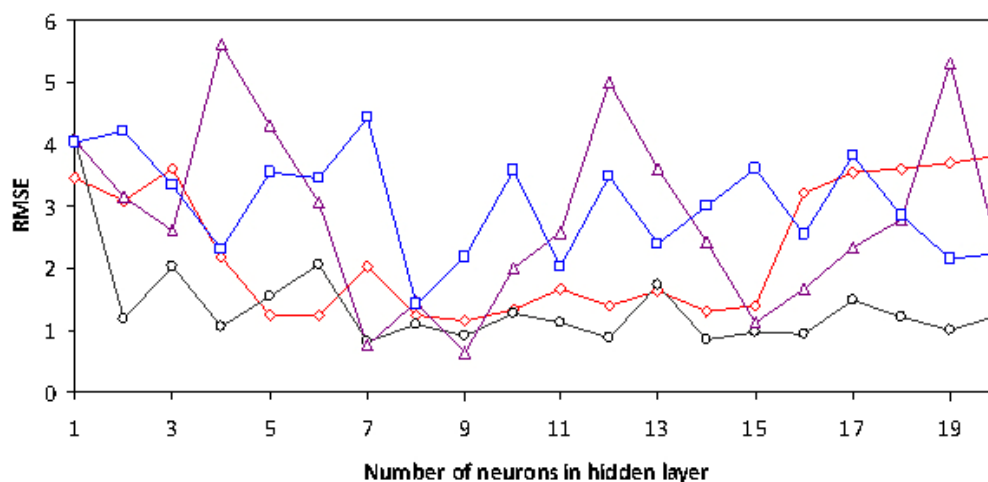


Figure 3. The performance of the network at different hidden neurons using:

- (◇) Incremental backpropagation (IBP) algorithm.
- (○) Batch backpropagation (BBP) algorithm.
- (△) Quick propagation (QP) algorithm.
- (□) Levenberg-Marquardt (LM) backpropagation algorithm.

that the most promising conditions can then be verified (Abdul Rahman et al. 2009).

The aim of the present work is to obtain an optimized ANN for predicting the yield of enzymatic acylation of betulinic acid with phthalic anhydride through a proper selection of the training algorithm. To do that, four training algorithms belonging to two broad classes have been evaluated: gradient descent algorithm, and Levenberg-Marquardt algorithm.

MATERIALS AND METHODS

Enzyme

Immobilized lipase (triacylglycerol hydrolase, EC 3.1.1.3; Novozym 435, 10000 PLU/g) from *Candida antarctica*, supported on a macroporous acrylic resin with a water content of 3% (w/w) was purchased from Novo Nordisk A/S (Bagsvaerd, Denmark).

Table 1. Experimental values (training, testing and validation data), actual and model predicted of isolated yield on the enzymatic reaction.

Run No.	Time (h)	Temperature (°C)	Amount of Enzyme (mg)	Molar ratio ¹	Isolated Yield (%)	
					Actual	predicted
Training Data						
1	8	50	150	0.6	33.3	33.28
2	24	50	150	0.6	58.8	58.85
3	16	40	150	0.6	31.1	31.11
4	16	50	50	0.6	39.8	39.78
5	16	50	250	0.6	43.1	43.15
6	16	50	150	0.2	29.5	29.51
7	12	45	100	0.4	20.2	20.24
8	20	45	100	0.4	36.5	36.49
9	20	55	100	0.4	47.4	47.39
10	12	45	200	0.4	27.6	27.57
11	20	45	200	0.4	43.2	43.15
12	12	45	100	0.8	35.6	35.58
13	20	45	100	0.8	49.1	49.11
14	12	55	100	0.8	55.2	55.22
15	12	45	200	0.8	40.8	40.81
16	20	45	200	0.8	58.6	58.54
17	12	55	200	0.8	52.5	52.44
18	20	55	100	0.8	62.7	62.64
19	16	60	150	0.6	53.3	53.3
20	16	50	150	1.0	58.9	58.94
21	16	50	150	0.6	54.7	54.57
Testing Data						
22	20	55	200	0.4	46.4	46.69
23	12	55	100	0.4	36.2	35.32
24	12	55	200	0.4	35.4	36.2
25	20	55	200	0.8	60.4	60.12
Validation Data						
26	24	45	176	1.0	57.5	58.11
27	24	50	176	1.0	60.5	60.23
28	24	55	176	1.0	61.8	61.34
29	24	60	176	1.0	57.3	58.12
30	20	53	148	0.8	64.3	64.91
31	20	54	145	0.9	64.7	65.65

¹Molar ratio = mmol betulinic acid/mmol phthalic anhydride

Solvents and substrates

Chloroform and *n*-hexane obtained from Fisher chemicals were used as the organic solvents. Betulinic acid was isolated from Malaysian *Callistemon speciosus* as our previous method (Ahmad et al. 1999). Phthalic anhydride was purchased from Acros, Belgium. Ethyl acetate, Celite[®]545, Na₂SO₄, K₂CO₃ and HCl was purchased from Merck, Germany. All chemicals were of analytical reagent grade.

Enzymatic esterification

The enzymatic reaction performed in this study is shown in Figure 1. To a magnetically stirred solution of betulinic acid (25 mg, 0.0547 mmol), K₂CO₃ (6 mg), Celite[®]545 (170 mg), different amounts of enzyme (50-250 mg), chloroform (10 ml) and *n*-hexane (10 ml) were added phthalic anhydride with difference molar ratio (mmol betulinic acid /mmol phthalic anhydride; 0.2-1). The reaction mixture was magnetically stirred (150 rpm) at

different reaction temperatures (40-60°C) and reaction times (8-24 hrs) as shown in Table 1. Each reaction was repeated in triplicate and results represented were the mean values of three independent experiments. Control experiments were performed in the absence of enzyme. As a result, no chemical acyl transfer reaction was detected.

Analytical procedures

TLC analysis. Qualitative analysis of reaction mixtures was made by thin layer chromatography (TLC) on silica gel plates eluted with system *n*-hexane/ethyl acetate (9:1, v/v). The plates were visualized under UV lamp and/or iodine vapor. Under these conditions, 3-*O*-phthalyl- betulinic acid had an R_f of 0.9.

Determination of 3-*O*-phthalyl- betulinic acid (2).

Quantitative analysis of samples was made according to the procedure described by Kvasnica et al. (2005). At predetermined time intervals, flasks were taken and enzyme was removed by filtration and washed twice with

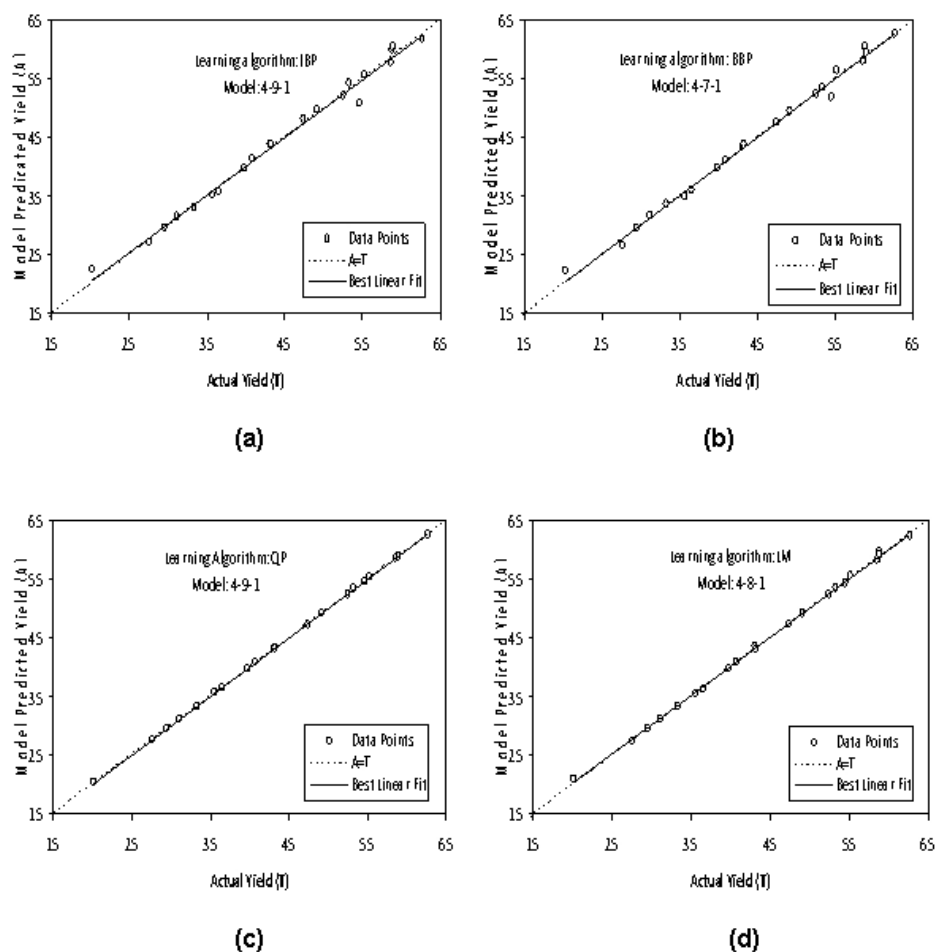


Figure 4. The scatter plots of ANN predicted yield versus actual yield for training data set from:

- Incremental backpropagation (IBP) algorithm.
- Batch backpropagation (BBP) algorithm.
- Quick propagation (QP) algorithm.
- Levenberg- Marquardt (LM) backpropagation algorithm.

chloroform. The filtrate was evaporated to dryness and ethyl acetate was then added and washed twice with aqueous solution of HCl and twice with water. The organic layer was dried over Na₂SO₄ and concentrated under reduced pressure. The residue was chromatographed with gradient on silica gel 60 (*n*-hexane/ethyl acetate, 9:1-5:1, v/v). The ester fractions were combined and weighed after evaporation of the solvents. The percentage isolated yield of ester (%Yield) is defined as:

$$\% \text{Yield} = \frac{\text{mmol isolated betulinic acid ester}}{\text{mmol used betulinic acid}} \times 100$$

[Equation 1]

Characterization of 3-O-phthalyl- betulinic acid (2). The product has been characterized by recording the ¹H & ¹³C-NMR spectra of the compound on a Varian Unity Inova 500 NMR spectrometer operating at 26°C and matched literature data (Kvasnica et al. 2005).

Experimental design and ANN modelling

Software tool. Commercially available NeuralPower, professional version 2.5 was employed in this study (CPC-X Software, 2004). This software is a Windows®-based package, which supports several types of training algorithms. NeuralPower operates via a graphical user interface (GUI) that enables the user to load the training and test sets, design the network architecture, select the training algorithm and generate the individual models for each output variable in a single operation (Ghaffari et al. 2006).

Data sets. The experimental data used for ANN design are presented in Table 1. The experimental data were randomly divided into two sets using the option available in the software: 21 of data sets were used as training data and four data sets were used as testing data. The training data was used to compute the network parameters. The testing data was used to ensure robustness of the network parameters. If a network “learns too well” from the training data, the

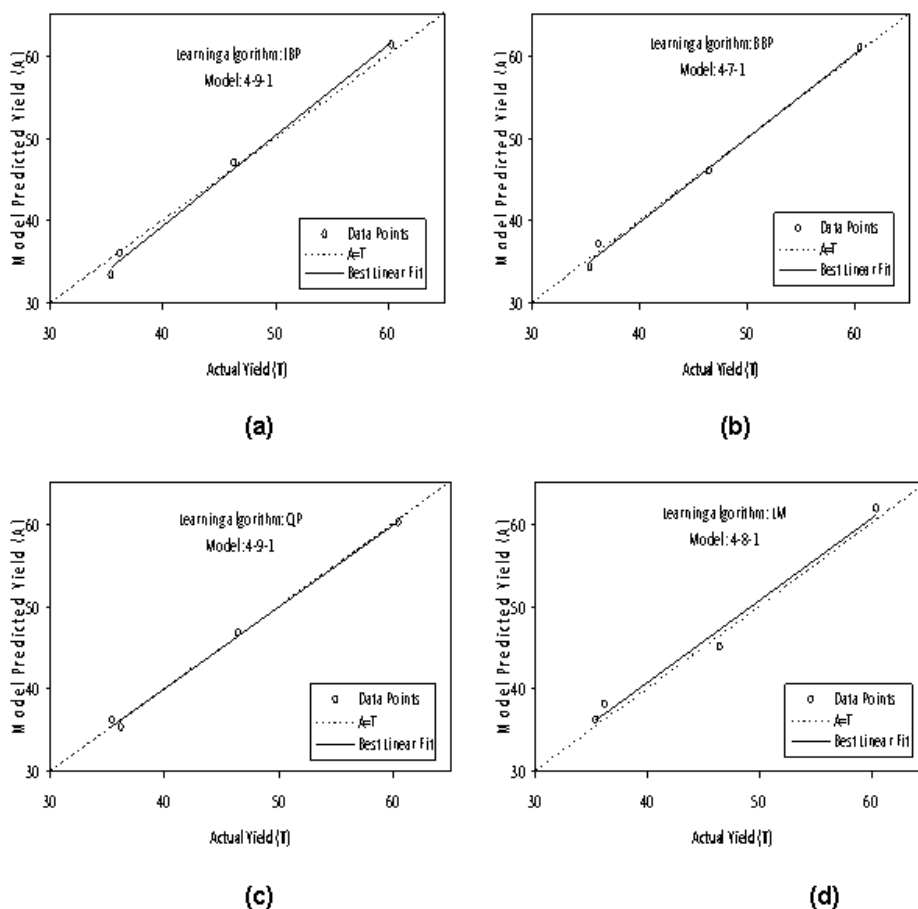


Figure 5. The scatter plots of ANN predicted yield versus actual yield for testing data set from:

- Incremental backpropagation (IBP) algorithm.
- Batch backpropagation (BBP) algorithm.
- Quick propagation (QP) algorithm.
- Levenberg- Marquardt (LM) backpropagation algorithm.

rules might not fit as well for the rest of the cases in the data. To avoid this “overfitting” phenomenon, the testing stage was used to control error; when it increased, the training was stopped (Song et al. 2004). Moreover, six additional experiments were carried out in the range of values given for ANN design. The data from these experiments were excluded from training and testing as unseen or “validation data” to assess the predictive ability of the generated model (Amani et al. 2008). The experimental data used for validation data (unseen data) are also presented in Table 1.

ANN description. In this study, a multi-layer perceptron (MLP) based feed-forward ANN which uses back-propagation learning algorithm, was applied for modeling enzymatic synthesis of 3-*O*-phthalyl- betulinic acid. This network is the most popular ANN (Cheng et al. 2008; Jorjani et al. 2008). The network consists of an input layer, hidden layers and an output layer. Inputs for the network are reaction time, reaction temperature, enzyme amount and substrate molar ratio; output is percentage isolated yield of ester. Feed-forward neural network usually has one or more hidden layers, which enable the network to model non-linear and complex functions (Jorjani et al. 2008). The number of hidden layers is difficult to decide (Ghaffari et al. 2006). It was reported in the literature that one hidden layer is normally adequate to provide an accurate prediction and can be the first choice for any practical feed-forward network design (Irie and Miyake, 1988; Cybenko, 1989; Hush and Horne, 1993; Shankar and Bandyopadhyay, 2007). Therefore, a single hidden layer network was used in this study. The structure of proposed ANN is shown in Figure 2.

The determination of number of neurons in hidden layers is very important as it affects the training time and generalization property of neural networks. A higher value of neurons in hidden layer may force the network to memorize (as opposed to generalize) the patterns which it has seen during training whereas a lower value of neurons in hidden layer would waste a great deal of training time in finding its optimal representation (Hussain et al. 1992). There is no general rule for selecting the number of neurons in a hidden layer. It depends on the complexity of the system being modelled (Cheng et al. 2008). The most popular approach to finding the optimal number of neurons in hidden layer is by trial and error (Ahmed, 2005). In this study, trial and error approach was used to determine the optimum neurons in hidden layer of the network (examined from 1 to 20 neurons).

Scaled data are passed into the input layer and then is propagated from input layer to hidden layer and finally to the output layer of the network (Hussain et al. 2002). Every node in hidden or output layer firstly acts as a summing junction which combines and modifies the inputs from the previous layer using the following equation (Jorjani et al. 2008):

$$y_i = \sum_{j=1}^i x_j w_{ij} + b_j \quad \text{[Equation 2]}$$

where y_i is the net input to node j in hidden or output layer, x_i are the inputs to node j (or outputs of previous layer), w_{ij} are the weights representing the strength of the connection between the i th node and j th node, i is the number of nodes and b_j is the bias associated with node j . Each neuron consists of a transfer function expressing internal activation level. Output from a neuron is determined by transforming its input using a suitable transfer function (Razavi et al. 2003). Generally, the transfer functions for function approximation (regression) are sigmoidal function, hyperbolic tangent and linear function (Jorjani et al. 2008). The most popular transfer function for non-linear relationship is the sigmoidal function (Bowen et al. 1998; Mohanty, 2005; Ghaffari et al. 2006; Shankar and Bandyopadhyay, 2007; Torrecilla et al. 2007). The general form of this function is as follows (Jorjani et al. 2008):

$$z_j = \frac{1}{1 + e^{-y_j}} \quad \text{[Equation 3]}$$

z_j , the output of node j , is also an element of the inputs to the nodes in the next layer. In this study, the sigmoidal function was used as the transfer function for the hidden and output layer nodes. The sigmoidal function is bounded between 0 and 1, so the input and output data should be normalized to the range 0 to 1 (Razavi et al. 2003). During training initial neural network, weights are chosen randomly. If one input has large number and another has a small number, but both show a similar amount of variance, then the network may ignore the small input due to the large contribution from the other input (Khare and Shiva Nagendra, 2007). Therefore, normalization (scaling) of data within a uniform range (*e.g.*, 0-1) is essential to avoid data with larger magnitude from overriding the smaller ones. Also, it is necessary to prevent premature saturation of hidden nodes, which impedes the learning process (Basheer and Hajmeer, 2000). Scaling of the data to the range 0-1 is carried out automatically within NeuralPower software.

There are many types of learning algorithms in the literature which can be used for training of the network (Krose and Smagt, 1996; Haykin, 1998; Christodoulou and Georgiopoulos, 2001). However, it is so difficult to know which learning algorithm will be more efficient for a given problem (Saracoglu, 2008). The algorithms used to train ANN in this study are standard or incremental backpropagation (IBP), batch backpropagation (BBP), quick propagation (QP) and Levenberg-Marquardt backpropagation (LM). These algorithms are belonging to two classes: gradient descent backpropagation algorithm

and Levenberg-Marquardt backpropagation algorithm. The details of the algorithms have been reported elsewhere (Ghaffari et al. 2006).

The learning rate and momentum coefficient for the networks were chosen as the default values of the NeuralPower software. Therefore, the default values of network for learning rate and momentum coefficient are 0.15 and 0.8 using incremental backpropagation (IBP) and 0.1 and 0.4 using batch backpropagation (BBP), respectively. The default value for learning rate using quick propagation (QP) is 0.8 and momentum coefficient is not employed in QP mode (Ghaffari et al. 2006).

Evaluation of model predictability. In order to perform a supervised training, a way in which the ANN output error between the actual and the predicted output could be evaluated is therefore required. A popular measure is the mean squared error (MSE) or root mean squared error (RMSE) (Ghaffari et al. 2006):

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - y_{di})^2 \quad \text{[Equation 4]}$$

$$RMSE = (MSE)^{\frac{1}{2}} \quad \text{[Equation 5]}$$

where n is the number of points, y_i is the predicted value obtained from the neural network model, y_{di} is the actual value.

The coefficient of determination, R^2 reflects the degree of fit for the mathematical model (Nath and Chattopadhyay, 2007). The closer the R^2 value is to 1, the better the model fits to the actual data (Sin et al. 2006):

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - y_{di})^2}{\sum_{i=1}^n (y_{di} - y_m)^2} \quad \text{[Equation 6]}$$

where n is the number of points, y_i is the predicted value obtained from the neural network model, y_{di} is the actual value, and y_m is the average of the actual values.

Absolute average deviation (AAD) is another important index to evaluate the ANN output error between the actual and the predicted output (Bas and Boyaci, 2007):

$$AAD = \left\{ \left[\sum_{i=1}^n (|y_i - y_{di}| / y_{di}) \right] / n \right\} \times 100 \quad \text{[Equation 7]}$$

where y_i and y_{di} are the predicted and actual responses, respectively, and n is the number of the points. The network having minimum RMSE, minimum AAD and maximum R^2 is considered as the best neural network model (Basri et al. 2007; Izadifar and Zolghadri Jahromi, 2007; Wang et al. 2008).

RESULTS AND DISCUSSION

ANN model training with gradient descent backpropagation algorithms

At first, the gradient descent backpropagation algorithms in three versions were used to train the neural networks. In order to determine the optimum number of neurons in hidden layer, a series of topologies was examined, in which the number of neurons was varied from 1 to 20. The root mean square error (RMSE) was used as the error function. Also, the coefficient of determination (R^2) and the absolute

Table 2. Statistical measures and performances of four learning algorithms on the enzymatic synthesis of betulinic acid ester.

Learning algorithm	The best architecture	Training data			Testing data		
		RMSE	R^2	AAD	RMSE	R^2	AAD
Quick Propagation (QP)	4-9-1	0.0335	0.9999	0.0647	0.6279	0.9961	1.4478
Incremental Backpropagation (IBP)	4-9-1	1.1738	0.9900	2.0796	1.1469	0.9871	2.2973
Batch Backpropagation (BBP)	4-7-1	0.9582	0.9933	1.7536	0.8096	0.9935	1.8932
Levenberg-Marquardt (LM)	4-8-1	0.2909	0.9993	0.5402	1.4214	0.9801	3.2160

average deviation (AAD) were used as a measure of the predictive ability of the network. Decision on the optimum topology was based on the minimum error of testing. Each topology was repeated five times to avoid random correlation due to the random initialization of the weights (Kasiri et al. 2008). After repeated trials, it was found that a network with 9 hidden neurons produced the best performances when IBP algorithm was employed. Similarly, the best results obtained with 9 hidden neurons using QP algorithm. However, a network with 7 hidden neurons produced the best results for BBP algorithm. These topologies have lowest RMSE for the training and testing sets. Figure 3 illustrates the performance of the network for testing data *versus* the number of neurons in the hidden layer using IBP, BBP and QP algorithms.

ANN model training with Levenberg-Marquardt backpropagation algorithm

Various topologies (from 1 to 20 hidden neurons) using Levenberg-Marquardt (LM) algorithm were examined. The results show that a network with 8 hidden neurons produced the best performances. The performance of the network for testing at different hidden neurons using LM algorithm is also shown in Figure 3.

Selection the best neural network model

The results for various algorithms are summarized and presented in Table 2. As shown in Table 2, the quick propagation algorithm has a better performance relative to incremental backpropagation, batch backpropagation and Levenberg-Marquardt backpropagation algorithms, because the best result derived from QP algorithm with 4-9-1 topology that has minimum RMSE, maximum R^2 and minimum AAD for both training and testing set. Figure 4 and Figure 5 show the scatter plots of ANN predicted yield *versus* actual yield with IBP, BBP, QP and LM algorithms for the training and testing sets, respectively. The predicted model using quick propagation algorithm was fitted so well to the actual values for both training and testing set. Therefore, it could be suggested that model trained with QP algorithm is the most efficient model for this problem; hence this model has been applied for further application. It was reported in literature that the quick propagation learning algorithm can be adopted for the training of all the ANN models (Jain et al. 2008). The predicted values of the best model for training and testing set are presented in Table 1.

Model validation

The predictive ability of generated model was estimated using validation data (unseen data) which were excluded from training. The actual and predicted yields for validation data are also presented in Table 1. The root mean squared error (RMSE) for validation data is 0.6626; the coefficient of determination (R^2) is 0.9488; and the absolute average deviation (AAD) is 1.0205. This results show that the

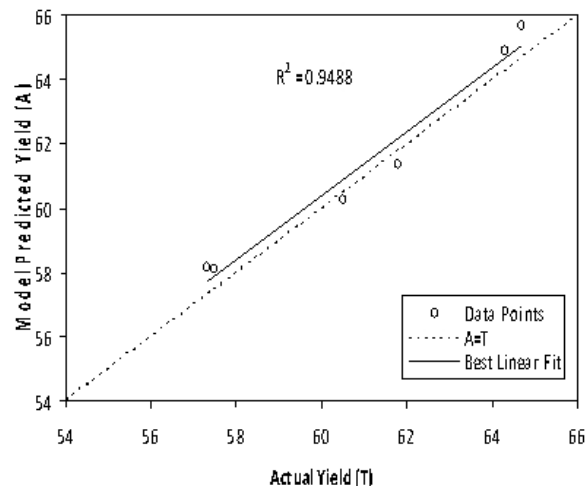


Figure 6. The scatter plot of ANN predicted yield *versus* actual yield for validation data.

predictive accuracy of the model is high. Figure 6 shows a comparison between actual values and model predicted output values using adopted neural network model for validating data.

CONCLUDING REMARKS

An artificial neural network for enzymatic synthesis of betulinic acid ester has been optimized through a proper selection of the training algorithm. Different ANNs, trained with standard or incremental backpropagation (IBP), batch backpropagation (BBP), quick propagation (QP) and Levenberg-Marquardt backpropagation (LM), have been evaluated with respect to their predictive ability. A robust comparison of the performances of the above four algorithms was made employing standard statistical indices. The results of this study show that the quick propagation algorithm implemented by NeuralPower software gave the best performances. The optimal configuration of the ANN model using quick propagation algorithm found to be 4-9-1. Therefore, it can be concluded that the ANN model described in this paper is an efficient quantitative tool to predict the isolated yield of ester in the enzymatic synthesis of betulinic acid ester. Finally, it was reported in literature that the appropriate selection of the training algorithm allows maximizing the predictive ability of the artificial neural network (Torrecilla et al. 2007). Thus, the results of this paper show that a correct selection of training algorithm is essential for successful data modeling using artificial neural network.

ACKNOWLEDGMENTS

The authors wish to thank all the staff in the Department of Chemistry of Universiti Putra Malaysia for their help in this study.

REFERENCES

- ABDUL RAHMAN, Mohd Basyaruddin; CHAIBAKHSH, Naz; BASRI, Mahiran; SALLEH, Abu Bakar and ABDUL RAHMAN, Raja Noor Zaliha Raja. Application of artificial neural network for yield prediction of lipase-catalyzed synthesis of dioctyl adipate. *Applied Biochemistry and Biotechnology*, September 2009, vol. 158, no. 3, p. 722-735.
- AHMAD, F.B.H; OMAR, J. and ALI, A.M. Chemical examination of local plant: triterpene from leaf of Malaysian *Callistemon speciosus* D.E. *Ultra Science*, 1999, vol. 11, p. 357-360.
- AHMED, Farid E. Artificial neural networks for diagnosis and survival prediction in colon cancer. *Molecular Cancer*, August 2005, vol. 4, no. 29.
- ALI AKCAYOL, M. and CINAR, Can. Artificial neural network based modeling of heated catalytic converter performance. *Applied Thermal Engineering*, October 2005, vol. 25, no. 14-15, p. 2341-2350.
- AMANI, Amir; YORK, Peter; CHRYSTYN, Henry; CLARK, Brain J. and DO, Duong Q. Determination of factors controlling the particle size in nanoemulsions using artificial neural networks. *European Journal of Pharmaceutical Sciences*, September 2008, vol. 35, no. 1-2, p. 42-51.
- BAS, Deniz and BOYACI, Ismail H. Modeling and optimization II: comparison of estimation capabilities of response surface methodology with artificial neural networks in a biochemical reaction. *Journal of Food Engineering*, February 2007, vol. 78, no. 3, p. 846-854.
- BAS, Deniz; DUDAK, Fahriye C. and BOYACI, Ismail H. Modeling and optimization IV: Investigation of reaction kinetics and kinetic constants using a program in which artificial neural network (ANN) was integrated. *Journal of Food Engineering*, April 2007, vol. 79, no. 4, p. 1152-1158.
- BASHEER, I.A. and HAJMEER, M. Artificial neural networks: fundamentals, computing, design, and application. *Journal of Microbiological Methods*, December 2000, vol. 43, no. 1, p. 3-31.
- BASRI, Mahiran; ABDUL RAHMAN, Raja Noor Zaliha Raja; EBRAHIMPOUR, Afshin; SALLEH, Abu Bakar; GUNAWAN, Erin Ryantin and ABD RAHMAD, Mohd Basyaruddin. Comparison of estimation capabilities of response surface methodology (RSM) with artificial neural network (ANN) in lipase-catalyzed synthesis of palm-based wax ester. *BMC Biotechnology*, August 2007, vol. 7, no. 53.
- BOWEN, W. Richard; JONES, Meirion G. and YOUSEF, Haitham N.S. Dynamic ultrafiltration of proteins-a neural network approach. *Journal of Membrane Science*, August 1998, vol. 146, no. 2, p. 225-235.
- CHENG, Jin; LI, Q.S. and XIAO, Ru-Cheng. A new artificial neural network-based response surface method for structural reliability analysis. *Probabilistic Engineering Mechanics*, January 2008, vol. 23, no. 1, p. 51-63.
- CHRISTODOULOU, Christos and GEORGIPOULOS, Michael. *Application of neural networks in electromagnetic*. USA; Artech House, 2001, 512 p. ISBN 978-0890068809.
- CPC-X Software, NeuralPower User Guide. Regsoft Inc., 2004. Available from Internet: <http://www.brothersoft.com/neuralpower-download-21356.html>
- CYBENKO, G. Approximation by superpositions of a sigmoidal function. *Mathematics of Control Signals and Systems*, December 1989, vol. 2, no. 4, p. 303-314.
- GAUTHIER, Charles; LEGAULT, Jean; LAVOIE, Serge; RONDEAU, Simon; TREMBLAY, Samuel and PICHETTE, André A. Synthesis of two natural betulinic acid saponins containing α -l-rhamnopyranosyl-(1 \rightarrow 2)- α -l-arabinopyranose and their analogues. *Tetrahedron*, July 2008, vol. 64, no. 30-31, p. 7386-7399.
- GHAFFARI, A.; ABDOLLAHI, H.; KHOSHAYAND, M.R.; SOLTANI BOZCHALOOI, I.; DADGAR, A. and RAFIEE-TEHRANI, M. Performance comparison of neural network training algorithms in modeling of bimodal drug delivery. *International Journal of Pharmaceutics*, December 2006, vol. 327, no. 1-2, p. 126-138.
- HAYKIN, Simon. *Neural networks: a comprehensive foundation*. 2th Ed., Englewood Cliffs, NJ; Prentice-Hall, 1999. 842 p. ISBN 978-0132733502.
- HUSH, D. and HORNE, B.G. Progress in supervised neural networks. *IEEE Signal Process Magazine*, January 1993, vol. 10, no. 1, p. 8-39.
- HUSSAIN, Mukhtar; BEDI, Jatinder S. and SINGH, Harpreet. Determining number of neurons in hidden layers for binary error correcting codes. In: *Proceedings of Applications of Artificial Neural Networks III* (21th April, 1992, Orlando, FL, USA). SPIE, 1992, p. 1015-1022.
- HUSSAIN, M.A.; SHAFIUR RAHMAN, M. and NG, C.W. Prediction of pores formation (porosity) in foods during drying: generic models by the use of hybrid neural network. *Journal of Food Engineering*, February 2002, vol. 51, no. 3, p. 239-248.
- IRIE, B. and MIYAKE, S. Capabilities of three-layered perceptrons. In: *Proceedings of International Conference on Neural networks* (24th - 27th July, 1988, San Diego, CA, USA). IEEE, 1988, p. 641-648.

- IZADIFAR, M. and ZOLGHADRI JAHROMI, M. Application of genetic algorithm for optimization of vegetable oil hydrogenation process. *Journal of Food Engineering*, January 2007, vol. 78, no. 1, p. 1-8.
- JAIN, Sanjay K.; SARKAR, Archana and GARG, Vaibhav. Impact of declining trend of flow on Harike Wetland, India. *Water Resources Management*, April 2008, vol. 22, no. 4, p. 409-421.
- JORJANI, E.; CHEHREH CHELGANI, S. and MESROGHLI, S.H. Application of artificial neural networks to predict chemical desulfurization of Tabas coal. *Fuel*, September 2008, vol. 87, no. 12, p. 2727-2734.
- KASIRI, M.B.; ALEBOYEH, H. and ALEBOYEH, A. Modeling and optimization of heterogeneous photo-fenton process with response surface methodology and artificial neural networks. *Environmental Science & Technology*, September 2008, vol. 42, no. 21, p. 7970-7975.
- KHARE, Mukesh and SHIVA NAGENDRA S.M. *Artificial neural networks in vehicular pollution modelling*. New York; Springer-Verlag Berlin Heidelberg, 2007. 242 p. ISBN 978-3-540-37418-3.
- KOSE, Erdogan. Modelling of colour perception of different age groups using artificial neural networks. *Expert Systems with Applications*, April 2008, vol. 34, no.3, p. 2129-2139.
- KROSE, Ben and SMAGT, Patrick van der. *An introduction to neural networks*. 8th Ed., Amsterdam; The University of Amsterdam, 1996, 133 p.
- KVASNICA, Miroslav; SAREK, Jan; KLINOTOVA, Eva; DZUBAK, Petr and HAJDUCH, Marian. Synthesis of phthalates of betulinic acid and betulin with cytotoxic activity. *Bioorganic & Medicinal Chemistry*, May 2005, vol. 13, no. 10, p. 3447-3454.
- LOUGHLIN, Wendy A. Biotransformations in organic synthesis. *Bioresource Technology*, August 2000, vol.74, no. 1, p. 49-62.
- MANDAL, Sumantra; SIVAPRASAD, P.V; VENUGOPAL, S. and MURTHY, K.P.N. Artificial neural network modeling to evaluate and predict the deformation behavior of stainless steel type AISI 304L during hot torsion. *Applied Soft Computing*, January 2009, vol. 9, no. 1, p. 237-244.
- MANOHAR, Balaraman and DIVAKAR, Soundar. An artificial neural network analysis of porcine pancreas lipase catalysed esterification of anthranilic acid with methanol. *Process Biochemistry*, October 2005, vol. 40, no. 10, p. 3372-3376.
- MOHANTY, Swati. Estimation of vapour liquid equilibria of binary systems, carbon dioxide-ethyl caproate, ethyl caprylate and ethyl caprate using artificial neural networks. *Fluid Phase Equilibria*, August 2005, vol. 235, no. 1, p. 92-98.
- MUKHERJEE, Rama; JAGGI, Manu; RAJENDRAN, Praveen; SRIVASTAVA, Sanjay K.; SIDDIQUI, Mohammad J.A.; VARDHAN, Anand and BURMAN, Anand C. Synthesis of 3-O-acyl/3-benzylidene/3-hydrazone/3-hydrazine/ 17-carboxyacryloyl ester derivatives of betulinic acid as anti-angiogenic agents. *Bioorganic & Medicinal Chemistry Letters*, June 2004, vol.14, no. 12, p. 3169-3172.
- MUKHERJEE, Rama; KUMAR, Vivek; SRIVASTAVA, Sanjay K.; AGARWAL, Shiva K. and BURMAN, Anand C. Betulinic acid derivatives as anticancer agents: structure activity relationship. *Anti-Cancer Agents in Medicinal Chemistry*, May 2006, vol. 6, no. 3, p. 271-279.
- NATH, A. and CHATTOPADHYAY, P.K. Optimization of oven toasting for improving crispness and other quality attributes of ready to eat potato-soy snack using response surface methodology. *Journal of Food Engineering*, June 2007, vol. 80, no. 4, p. 1282-1292.
- RAJENDRAN, Praveen; JAGGI, Manu; SINGH, Manoj K.; MUKHERJEE, Rama and BURMAN, Anand C. Pharmacological evaluation of C-3 modified betulinic acid derivatives with potent anticancer activity. *Investigational New Drugs*, February 2008, vol. 26, no. 1, p. 25-34.
- RAZAVI, Mohammad A.; MORTAZAVI, Ali and MOUSAVI, Mahmoud. Dynamic modeling of milk ultrafiltration by artificial neural network. *Journal of Membrane Science*, August 2003, vol.220, no. 1-2, p. 47-58.
- SARACOGLU, O. Galip. An artificial neural network approach for the prediction of absorption measurements of an evanescent field fiber sensor. *Sensors*, March 2008, vol. 8, no. 3, p. 1585-1594.
- SHANKAR, T.J. and BANDYOPADHYAY, S. Prediction of extrudate properties using artificial neural networks. *Food and Bioproducts Processing*, March 2007, vol. 85, no. 1, p. 29-33.
- SILVA, James A.; COSTA NETO, Edilson Holanda; ADRIANO, Wellington S.; FERREIRA, Andrea L.O. and GONÇALVES, Luciana R.B. Use of neural networks in the mathematical modelling of the enzymic synthesis of amoxicillin catalysed by penicillin G acylase immobilized in chitosan. *World Journal of Microbiology & Biotechnology*, September 2008, vol. 24, no. 9, p. 1761-1767.
- SIN, H.N.; YUSOF, S.; SHIKH ABDUL HAMID, N. and ABDU. RAHMAN, R. Optimization of enzymatic clarification of sapodilla juice using response surface

methodology. *Journal of Food Engineering*, April 2006, vol. 73, no. 4, p. 313-319.

SONG, Xiaowei; MITNITSKI, Arnold; MACKNIGHT, Chris and ROCKWOOD, Kenneth. Assessment of individual risk of death using self-report data: an artificial neural network compared with a frailty index. *Journal of the American Geriatrics Society*, July 2004, vol. 52, no. 7, p. 1180-1184.

SZALENIEC, Maciej; WITKO, Małgorzata; TADEUSIEWICZ, Ryszard and GOCLON, Jakub. Application of artificial neural networks and DFT-based parameters for prediction of reaction kinetics of ethylbenzene dehydrogenase. *Journal of Computer-Aided Molecular Design*, March 2006, vol. 20, no. 3, p. 145-157.

THIBEAULT, Dominic; GAUTHIER, Charles; LEGAULT, Jean; BOUCHARD, Jimmy; DUFOUR, Philippe and PICHETTE Andre. Synthesis and structure-activity relationship study of cytotoxic germanicane and lupane-type 3 β -O-monodesmosidic saponins starting from betulin. *Bioorganic & Medicinal Chemistry*, September 2007, vol.15, no. 18, p. 6144-6157.

TORRECILLA, J.S.; OTERO, L. and SANZ, P.D. Optimization of an artificial neural network for thermal/pressure food processing: Evaluation of training algorithms. *Computers and Electronics in Agriculture*, April 2007, vol. 56, no. 2, p. 101-110.

WANG, Lingzhao; YANG, Bao; WANG, Rui and DU, Xiuqiao. Extraction of pepsin-soluble collagen from grass carp (*Ctenopharyngodon idella*) skin using an artificial neural network. *Food Chemistry*, December 2008, vol. 111, no. 3, p. 683-686.

YASIN, Yamin; BASRI, Mahiran; FAUJAN, Ahmad and SALLEH, Abu Baker Salleh. Response surface methodology as a tool to study the lipase-catalyzed synthesis of betulinic acid ester. *Journal of Chemical Technology and Biotechnology*, February 2008, vol. 83, no. 5, p. 694-698.

YOGESWARI, Prumal and SRIRAM, Dharmarajan. Betulinic acid and its derivatives: a review on their biological properties. *Current Medicinal Chemistry*, 2005, vol. 12, no. 6, p. 657-666.

ZAREVUKA, Marie and WIMMER, Zdenek. Plant products for pharmacology: Application of enzymes in their transformations. *International Journal of Molecular Sciences*, December 2008, vol. 9, no. 12, p. 2447-2473.