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ARTICLE *in* INDUSTRIAL & ENGINEERING CHEMISTRY RESEARCH · SEPTEMBER 2011

Impact Factor: 2.59 · DOI: 10.1021/ie200900z

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Artificial Neural Networks Applied for Simultaneous Analysis of Mixtures of Nitrophenols by Conductometric Acid−Base Titration

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ABSTRACT: In this study, the simultaneous conductometric titration method for determination of mixtures of 4-nitrophenol, 2,4-dinitrophenol, and 2,4,6- trinitrophenol based on principal component artificial neural network (ANN) calibration model was proposed. The three-layered feed-forward ANN trained by back-propagation learning was used to model the complex nonlinear relationship between the concentration of 4-nitrophenol, 2,4-dinitrophenol, and 2,4,6-trinitrophenol in their ternary mixtures and the conductance of the solutions at different volumes of titrant. The principal components of the conductance matrix were used as the input of the network. The network architecture and parameters were optimized to give low prediction error. The optimized networks predicted the concentrations of nitrophenols in synthetic mixtures. The results showed that the used ANN can proceed the titration data with low relative prediction errors (5.53%, 4.03%, and 4.71% for 4-nitrophenol, 2,4-dinitrophenol, and 2,4,6-trinitrophenol, respectively) and satisfactory recoveries.

INTRODUCTION

Among the transduction methods developed, conductometric transducer is quite simple and is easily fabricated because it has no reference electrode.[1] Nowadays, almost in all industrial plants and clearly in all research analytical laboratories, there is a digital conductomer that is computer controlled. Conductometry is a relatively inexpensive, simple, and accurate method. Conductometric titrations have a more selective character when acid−base,[2] complexometric,[3,4] or precipitation[5,6] reactions are explored, thus widening the range of analytical applications.

In binary or ternary mixtures of acids or bases, if the differences between acidity constants of individual acids are less than four logarithmic units, we cannot observe all of the titration end points. So, it is impossible to have an accurate determination in these types of mixtures.

Introducing the multivariate statistical methods in analytical chemistry creates a suitable and easy to use device to tackle and remove such problems. That these methods used a whole data set in the course of titration (first-order method) instead of a single or scalar datum (zero-order methods such as end point in conventional titrations) gave good capability to these approaches to determine the concentrations of all constituents of a mixture.

The application of multivariate calibration to potentiometric titration data was introduced by Lindberg and Kowalski[7] in 1988 for the simultaneous determination of acid mixtures using acid−base titration and partial least-squares (PLS) regression. After that, this PLS calibration method has been applied to complexometric titration,[8] pH metric titration,[9] potentiometric precipitation titration,[10] and conductometric titration[11] by different researchers.

In these methods, the authors assumed a linear relationship between the volume of titrant added and analytes concentrations.

Coelho and Gutz introduced a chemometric method based on multiparametric nonlinear regression for simultaneous analysis of acids and bases by conductometric titration.[12] This proposed method became difficult when only conductometric measurements were available but could be elegantly solved by using auxiliary pH data, collected simultaneously during the titration.

The assumed linear relationship, however, becomes complicated in the complex acid−base systems and interactions between components in the titration vessel. To overcome this problem, some researchers used ANN to treat potentiometric acid−base titration.[13,14]

In recent years, artificial neural network (ANN) as a powerful nonparametric nonlinear modeling technique has attracted much interest and becomes an increasingly popular technique to nonlinear calibration for multicomponent determination.[15,16]

The artificial neural networks (ANNs) approach has several advantages over the multivariate calibration including easy programming of the network architecture, not necessary for any priori assumption on the behavior of the data, ability to process input data containing some degree of uncertainty and handling nonlinearity due to analyte−analyte interaction, the synergistic effect, and so on.[17−21]

The most popular method for data compression in chemometrics is principal component analysis (PCA). In practice, principal components (PCs) are often successfully used as inputs. Even if there is some nonlinearity in the data set, all relevant information is usually contained in the first PCs.[17] The application of an ANN model with data pretreatment method, such as normalization[22] and compressing data into scores with the use of PCA (PC-ANN) as input data to quantify mixtures in different situations, has been reported.[23,24] Reducing the number of inputs to a network reduces the training time and repetition in the input data.[25−27]

Phenolic compounds are some of the most important contaminates present in the environment as a result of various processes

Received: April 27, 2011
Accepted: August 11, 2011
Revised: July 28, 2011
Published: August 17, 2011

dx.doi.org/10.1021/ie200900z | *Ind. Eng. Chem. Res.* 2011, 50, 11375–11381

such as plastics, dyes, pesticides, paper, and petrochemical products.[28−31] Phenols as a class of organics are similar in structure to the more common herbicides and insecticides in that they are resistant to biodegradation. Some waterways can be contaminated for phenols, and hazardous effects may occur to the people, and also to aquatic organisms, fish, and other life forms.[32]

4-Nitrophenol is used mainly to make drugs, fungicides, dyes, and to darken leather. Commercial dinitrophenols are primarily used for scientific research and in manufacturing. They have been used at times to make dyes, other organic chemicals, and wood preservatives. It has also been used to make photographic developer, explosives, and pesticides.

2,4,6-Trinitrophenol (picric acid) is frequently found in forensic laboratories for use as Christmas tree stain[33] and for urine detection.[34] It is also used in medicinal formulations in the treatment of malaria, trichinosis, herpes, smallpox, and antiseptics. Industrial production of polynitroaromatics over several decades has resulted in contamination of soil, ground, surface, and wastewaters. These compounds have a toxic effect on humans, animals, and plants, and they give an undesirable taste and odor to drinking water, even at very low concentration. Hence, the determination of trace nitrophenols is very important. Several methods, such as spectrophotometry,[35,36] electrochemical method,[37−39] chromatographic techniques associated with mass spectrometry,[40,41] gas chromatography,[42,43] and capillary electrophoresis,[44] have been described in the literature for detection of nitrophenols. However, some of these techniques are expensive, time-consuming, and need skilful operators and sometimes require preconcentration and extraction steps that increase the risk of sample loss.

In this work, the nonlinear relationship between conductivity values and analytes (i.e., 4-nitrophenol, 2,4-dinitrophenol, and 2,4,6-trinitrophenol) concentrations was observed. We then used a three-layer ANN with back-propagation of error algorithm for modeling the complex relationship between measured conductance and concentration through a multicomponent acid −base titration. To decrease the number of data points, the data were factor analyzed before entering into ANN. The extracted significant principal components from the original data were used as input of neural network. The aim of this work was to propose the conductometric titration method to resolve mixtures of weak acids with similar pK_a in synthetic mixtures without prior separation. The method was applied to simultaneous determination of three weak organic acids (i.e., 4-nitrophenol, 2,4-dinitrophenol, and 2,4,6-trinitrophenol) in their ternary mixtures, and satisfactory results were obtained.

EXPERIMENTAL SECTION

The conductometric titrations were carried out in a double walled cell, and the temperature was kept constant using a water bath circulating system at a constant temperature of 25 °C. The conductance was measured by a digital conductometer (Amel, model 60). The electrolytic conductance was measured using a cell consisting of two platinum electrodes to which an alternating potential was applied. The cell constant was 0.73 cm^{-1}. The mathematical program MATLAB 7.6.0 (R2008a) (Math Works, Cochituate Place, MA) was used for data processing. Neural networks were implemented in Neural Power, professional version 2.5 (CPC-X Software, 2004). This software is a Windows-based package, which supports several types of training algorithms.

Reagent and Solutions. All reagents used were of analytical reagent grade prepared from Merck Co. All solutions were prepared with doubly distilled water. The stock solutions of 0.01 mol L^{-1} 4-nitrophenol, 2,4-dinitrophenol, and 2,4,6-dinitrophenol were prepared by dissolving the appropriate amount of each compound in water. Sodium hydroxide solution of 0.05 mol L^{-1} was prepared as the titrant. These solutions were used in both calibration, prediction, and validation steps, so no standardized procedure was necessary. Standards of working solution were made by appropriate dilution daily as required.

Procedure. In a typical titration, 25 mL of the solution containing suitable amounts of individual acids or acid mixtures was placed in a 50 mL vessel. The solution was then stirred and titrated with the 0.05 mol L^{-1} sodium hydroxide solution using a microburett. The conductance of the solution was recorded after each 0.1 mL addition of titrant. For each solution, 50 data points were recorded.

Data Processing. The data matrix used as input for the neural network was conductance of standard solutions in different volumes of sodium hydroxide solution at 0.1 mL intervals. Because the high number of nodes in the input layer of the network increases the CPU time for ANN modeling and the number of data values used for training must exceed that of weights determined in the network,[45] the data matrix was factor analyzed before being introduced into the network.[46]

Consider that the data matrix ($\mathbf{D}$) has the dimension of $n \times m$, where n and m are the number of standard solutions and the number of conductance readings for each solution, respectively. The score and loading of this matrix were calculated by the singular value decomposition (SVD) as follows:[47]

$$\mathbf{D} = \mathbf{USV}' \quad (1)$$

$$\mathbf{T} = \mathbf{US} \quad (2)$$

$$\mathbf{P} = \mathbf{V} \quad (3)$$

The prime denotes the transpose of the matrix. $\mathbf{T}$ and $\mathbf{P}$ are the score and loading whose dimensions are $n \times n$ and $m \times n$, respectively. The original data matrix can be reproduced by considering only the first r significant principal components of score, $\overline{\mathbf{T}}$, and loading, $\overline{\mathbf{P}}$, matrix.[48]

$$\bar{\mathbf{D}} = \overline{\mathbf{T}}\overline{\mathbf{P}}' \quad (4)$$

where $\overline{\mathbf{T}}$ and $\overline{\mathbf{P}}$ have the dimensions of $n \times r$ and $m \times r$, respectively. In the calibration step, the input of neuron was the abstract score, $\overline{\mathbf{T}}$, instead of the original data matrix. In the prediction step, the score, $\overline{\mathbf{T}}\mathbf{p}$, of the data matrix of the prediction set, $\mathbf{D}_p$, was calculated as follows:

$$\overline{\mathbf{T}}\mathbf{p} = \bar{\mathbf{D}}_p \cdot \overline{\mathbf{P}} \quad (5)$$

ANN Modeling. ANNs are known methods for solving overlapping and nonlinear problems.[49] An ANN generally comprises an input layer, an output layer, and between the two layers, there are one or more hidden layers.[50] Feed-forward back-propagation neural network (BP-ANN) has good capacity for training and prediction,[51] so it was used for the training process due to its advantages.

The ANN method, which was trained with the back-propagation of errors learning algorithm, was run on the calibration data constructed with principal component analysis.

The network consists of three layers, the input layer, the hidden layer in which the number of nodes would be determined

during training and prediction, and the output layer with a simple output node, which contained the concentration of nitrophenol sought for the chemical system studied. A bias is used to calculate the net input of a node from all of the nodes connected to it.

Each layer is formed by a series of interconnected neurons, and the value at each neuron was weighted and transformed by a transfer function. The input nodes transfer the weighted input signals to the nodes in the hidden layer, and the same as the hidden nodes for the output layers. A connection between the nodes of different layers was represented by a weight, w_{ij}, and, during the training process, the connection of weight is performed according to the delta rule. Assume that

$$\mathbf{C} = f(\mathbf{D}) \tag{6}$$

where $\mathbf{D}(n \times m)$ represents the measured data matrix. $\mathbf{C}(n \times p)$ denotes the corresponding concentration matrix with each row expressing the concentration vector for one known mixture sample containing p distinct components in the training set. The task for the BP-ANN technique is to find a nonlinear mapping, denoted by f in eq 6, which specifies the mathematical relationship between matrices $\mathbf{C}$ and $\mathbf{D}$. This procedure is known as supervised training in BP-ANN in which the network is trained to generate correct outputs from inputs. After this mathematical relationship f has been determined, one can easily find the concentration matrix of an unknown sample, $\mathbf{C}_{\text{unknown}}(k \times p)$, from the corresponding measured data matrix, $\mathbf{D}_{\text{unknown}}(k \times m)$, according to the following equation:

$$\mathbf{C}_{\text{unknown}} = f(\mathbf{D}_{\text{unknown}}) \tag{7}$$

This procedure, defined by eq 7, is known as the prediction step in BP-ANN. The training procedure, defined by eq 6, is achieved by supervised learning, which corrects weights after one sample spectrum (or a multivariate signal) passes through the network. The correction of weights is based on the error (difference) between the desired target and the actual output. The iteration would be finished when the error of prediction reached a minimum.[52]

RESULTS AND DISCUSSION

Three types of nitrophenols were used as the analytes in this study. The acids used in this study are chemically related compounds, and they have close acidity constants. The pK_a values of 4-nitrophenol, 2,4-dinitrophenol, and 2,4,6-trinitrophenol are 7.15, 4.08, and 0.30, respectively.

Figure 1 shows the conductometric titration curves of these phenols and their mixture. It is obvious that the neutralization steps in the titration curves of these three acids (in their mixture) are overlapped. To overcome this drawback for simultaneous determination and removing the interference effects of one component in the presence of others, multivariate calibration approaches were applied.

The first step in simultaneous determination of different species by multivariate methods involves constructing the calibration set for mixtures of them. The multivariate calibration requires a careful experimental design of the standard composition of calibration set to provide the best predictions. To select the mixtures that provide more information using a few experimental trials, from the calibration set, the orthogonal array design (L_{16}) was applied for the construction of the set of calibration samples.[53] Table 1 shows the composition of 16 calibration samples, which were designed according to a four-level orthogonal array design.

Another 10 ternary synthetic mixtures containing the three analytes mixed in randomly selected ratios were also prepared as a prediction set (Table 1). The prediction set is used to determine

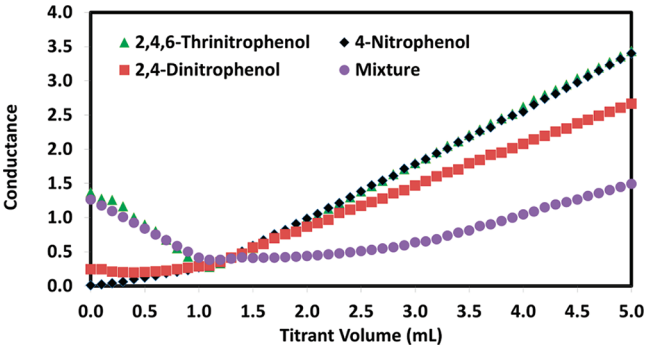

Figure 1. Titration curves for 2,4,6-trinitrophenol (2 mmol L^{-1}), 2,4-dinitrophenol (2 mmol L^{-1}), and 4-nitrophenol (2 mmol L^{-1}) and their mixtures with sodium hydroxide solution (0.05 mol L^{-1}).

Table 1. Composition of Calibration, Prediction, and Validation Samples in Ternary Mixtures of Nitrophenols

	concentration (mmol L^{-1})								
	calibration set			prediction set			validation set		
sample number	4-Nph[a]	2,4-diNph[b]	2,4,6-triNph[c]	4-Nph	2,4-diNph	2,4,6-triNph	4-Nph	2,4-diNph	2,4,6-triNph
1	0.5	0.5	0.5	1.6	1.4	1.3	1.6	1.0	1.4
2	0.5	1.0	1.0	1.8	1.9	0.6	1.8	0.8	0.9
3	0.5	1.5	1.5	1.6	1.9	1.7	1.3	1.8	0.6
4	0.5	2.0	2.0	1.8	1.0	1.9	1.8	1.6	1.4
5	1.0	0.5	1.0	1.3	1.6	1.4	1.3	1.9	1.5
6	1.0	1.0	0.5	1.4	0.6	1.5	0.6	1.3	1.6
7	1.0	1.5	2.0	0.6	0.8	1.5	0.6	1.4	1.4
8	1.0	2.0	1.5	1.1	1.8	0.8	1.1	1.7	0.6
9	1.5	1.5	0.5	1.9	1.6	1.3	1.9	1.9	1.9
10	1.5	0.5	1.5	2.0	1.9	1.5	1.9	1.4	1.3
11	1.5	1.0	2.0						
12	1.5	2.0	1.0						
13	2.0	0.5	2.0						
14	2.0	1.0	1.5						
15	2.0	1.5	1.0						
16	2.0	2.0	0.5						

[a] 4-Nitrophenol. [b] 2,4-Dinitrophenol. [c] 2,4,6-Trinitrophenol.

the performance of a neural network on patterns that are trained during the learning.

The 10 synthetic mixtures of analytes (validation set) that were not included in the previous sets were employed as an independent test for finally checking the overall performance of a neural network, and also to validate the prediction ability of different chemometrics methods. The validation set was chosen randomly (Table 1). That is, the digitized conductances of the calibration mixtures were gathered in a 16 × 50 data matrix, and conductances of prediction and validation matrixes were collected in two 10 × 50 data matrices.

Comparison of Different Multivariate Linear Models. In the first CLS, PCR, and PLS1 methods, algorithms were used to model the concentration of the analytes.

To investigate the uncertainty of prediction for each calibration method, the relative prediction error (RPE)[54] and recovery

values parameters were calculated. The RPE for a single component in the mixtures can be formulated as:

$$\mathrm{RPE_S} = \left[\frac{\sum_{i=1}^{n}\left(c_{\mathrm{pred},i,j} - c_{\mathrm{real},i,j}\right)^2}{\sum_{i=1}^{n}\left(c_{\mathrm{real},i,j}\right)^2}\right]^{0.5} \quad (8)$$

and the $\mathrm{RPE_T}$ for all components can be formulated as:

$$\mathrm{RPE_T} = \left[\frac{\sum_{i=1}^{n}\sum_{j=1}^{m}\left(c_{\mathrm{pred},i,j} - c_{\mathrm{real},i,j}\right)^2}{\sum_{i=1}^{n}\sum_{j=1}^{m}\left(c_{\mathrm{real},i,j}\right)^2}\right]^{0.5} \quad (9)$$

where n is the number of samples, and $c_{\mathrm{real},i,j}$ indicates the concentration of jth component in ith mixture and $c_{\mathrm{pred},i,j}$ is its estimate found by chemometric methods.

The recovery of the predicted concentration was calculated as:

$$\text{recovery } (\%) = 100 \times \left(\frac{c_{\mathrm{pred},i,j}}{c_{\mathrm{real},i,j}}\right) \quad (10)$$

Yet these methods (CLS, PCR, and PLS1) performed poor, and there were not good and acceptable agreement between the obtained and real concentrations of validation set. They gave high $\mathrm{RPE_T}$ and $\mathrm{RPE_s}$ (more than 30% for three of analytes), and the recoveries were also not satisfactory. These methods generally cannot account for any nonlinearity between components; they do not model well complex analytical systems. Several data pretreatments such as transformation of the raw data (titration curves) to their derivatives (first and second) and mean centering were checked to enhance the linear relationship between conductance and concentration of acids in calibration model building. Also, we used the squares and other power of the concentration values (C^n) instead of original concentration values. Yet it was found that the prediction errors did not improve.

Artificial Neural Network Architecture and Optimization. ANNs are among the best known methods for solving overlapping and nonlinear problems, whose structure is designed to imitate the organization of human brain.[55]

To obtain the best network performance, the optimal network architecture and parameters (number of input neurons or PCs in this study, number of hidden neurons, learning rate, momentum, and number of epochs) must be chosen to reduce the effect of the random initial starting conditions.

An exhaustive study of the network model structure was done to optimize the separate determination of the three nitrophenol concentrations.

Selecting the optimum parameter values for constructing a network is no easy task; in fact, the parameters are mutually related, so a compromise must usually be adopted. The root-mean-quare errors prediction (RMSEP) was used as criterion for finalizing the learning process.[56] The training was stopped manually when the root-mean-square error of the prediction increased after successive iteration. The results obtained in the quantification of the samples in the training and prediction sets are expressed as:

$$\mathrm{RMSEP}_{(j)} = \sqrt{\frac{\sum_{i=1}^{n}\left(c_{\mathrm{pred},i,j} - c_{\mathrm{real},i,j}\right)^2}{n}} \quad (11)$$

where n is the number of prediction set samples.

The RMSEP value measures how good output values ($c_{\mathrm{pred},i,j}$) are in comparison with the target values ($c_{\mathrm{real},i,j}$).

The aim of any training is to reach the smallest RMSEP values as possible in the shortest possible time. The ANN models that provided the lowest RMSEP for the prediction set were chosen. Overfitting is avoided by using two sets of samples; thus, weights are calculated from a calibration set, while the concentration of another sample set (prediction set) is being simultaneously predicted. However, random initial values will lead to variability in the performance of network with exactly the same program. So we ran each ANN program more than three times and averaged the RMSEPs for the external test set to obtain a true measure of performance for it.

Studies of the network structure include the selection of the number of layers and number of nodes in each layer. The number of layers used for this neural network modeling was three, that is, an input layer, a hidden layer, and an output layer. Because it was stated that an appropriate level of modeling could be achieved with a single hidden layer in the electrochemical signal resolving process in the relative literature,[57] networks with more than one hidden layer were not considered.

If the number of weights exceeds the number of samples for the training of ANN to some extent, "overfitting" may be caused.[58] Also, in the case of a high number of input variables, meaningful variables could be hidden,[59] and the probability of chance correlation increases,[60] which may prevent ANN from finding optimized models.[61]

Therefore, PCA input selection is necessary to improve the predicted results of ANN. Therefore, the conductometric data, before building the ANNs models, were subjected to principal component analysis and decomposed to PC scores. PC-ANN not only simplifies the training procedure of ANN by reducing the dimensions of the measured data without losing any useful information, but also reflects its ability to account for extraneous noise in the calibration set.[45]

The number of neurons in the input layer, which was the number of significant principal components of the original data matrix, were optimized for each nitrophenol separately. The number of significant principal components was not used as input, because the magnitude of an eigenvalue is not necessarily a measure of its significance for the calibration.[62] The ANNs including one to eight PC scores were trained. The lowest RMSEP values were obtained with four, five, and four input factors for 4-nitrophenol, 2,4-dinitrophenol, and 2,4,6-trinitrophenol, respectively. The most accurate networks are those that have a limited number of hidden neurons.[45] To determine the optimal number of hidden layer networks, neural networks with different numbers of hidden nodes were trained. The number of hidden nodes was varied from one to nine to train the networks. According to RMSEP values versus the number of hidden layer nodes, the best number of hidden layer nodes were four, four, and five for 4-nitrophenol, 2,4-dinitrophenol, and 2,4,6-trinitrophenol, respectively (Figure 2). The output layer had only one node (i.e., the concentration of desired nitrophenol).

The other network parameters that should be optimized, to get the best network architecture and to reduce the effect of the random initial starting conditions, are transfer functions in the layers used by each neuron, number of epochs, momentum, and learning rate.

Different transfer functions in the hidden and output layers were also tested: linear transfer function such as (pure) linear, threshold linear, and bipolar linear function and nonlinear transfer function such as sigmoid, hyperbolic tanh, and Gaussian function. In our network, it was found that the sigmoid transfer

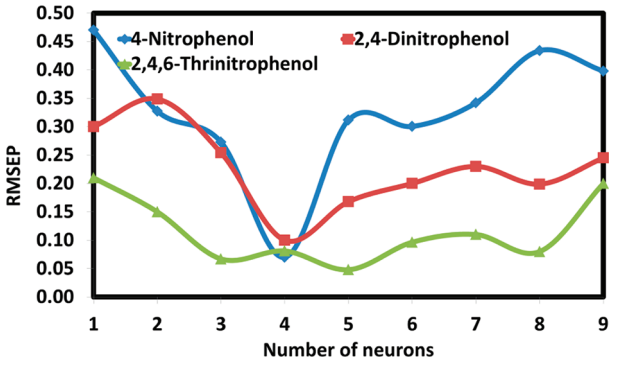

Figure 2. Plot of RMSEP as a function of the number of neurons in the hidden layer for 2,4,6-trinitrophenol, 2,4-dinitrophenol, and 4-nitrophenol.

Table 2. Optimized Parameters Used for Construction of PC-ANN for Simultaneous Determination of 4-Nitrophenol, 2,4-Dinitrophenol, and 2,4,6-Trinitrophenol

parameter	4-nitrophenol	2,4-dinitrophenol	2,4,6-trinitrophenol
input neurons	4	5	4
hidden neurons	4	4	5
output neurons	1	1	1
hidden layer transfer function	sigmoid	sigmoid	sigmoid
output layer transfer function	sigmoid	sigmoid	sigmoid
learning rate	0.80	0.75	0.30
number of iteration (epochs)	85 000	60 000	50 000
momentum	0.40	0.25	0.10

function (with slope 1) in the hidden and output layers had a better performance than did the other transfer functions. Generally, in ANN modeling research, the sigmoid function is the most versatile transfer function that can be used to model a variety of nonlinear relationships.[17,63]

In the hidden layer, the weighted inputs were summed and transformed by a sigmoid transfer function, and the data of hidden layer were also weighted and summed by sigmoid transfer function to give the output, which had only one node.[17] The weights of hidden and output layers were adjusted by back-propagation of the error algorithm.

The optimum learning rate was evaluated, in the range of 0.1−1, by obtaining those that yielded a minimum in the error of prediction. If the learning rate for each network was set too high, the network became unstable and divergent. As is obvious from Table 2, the optimum learning rates for 4-nitrophenol, 2,4-dinitrophenol, and 2,4,6-trinitrophenol are 0.80, 0.75, and 0.30, respectively.

The optimum number of iterations (epochs) for each component was also obtained. A minimum in RMSEP occurred by using 85 000, 60 000, and 50 000 iterations for 4-nitrophenol, 2,4-dinitrophenol, and 2,4,6-trinitrophenol, respectively. Continued training beyond these values causes the RMSEP to level off or increase slowly.

Momentum values were also varied between 0.1−1 in the hopes of finding what would give the most rapid optimization of network. The optimum and momentum were evaluated by obtaining those that yielded a minimum in RMSEP.

The characteristics of the optimized networks used to model the titration data are summarized in Table 2.

Table 3. Estimated and Actual Concentrations of 4-Nitrophenol, 2,4-Dinitrophenol, and 2,4,6-Trinitrophenol in Prediction Samples by Optimized PC-ANN Model

	concentration (mmol L^{-1})								
	4-Nph			2,4-Nph			2,4,6-triNph		
sample number (prediction set)	actual	found	rec.[a] (%)	actual	found	rec. (%)	actual	found	rec. (%)
1	1.6	1.55	96.9	1.4	1.36	97.1	1.3	1.30	100.0
2	1.8	1.85	102.8	1.9	1.93	101.6	0.6	0.56	93.3
3	1.6	1.56	97.5	1.9	1.94	102.1	1.7	1.65	97.1
4	1.8	1.84	102.2	1.0	0.99	99.0	1.9	2.01	105.8
5	1.3	1.27	97.7	1.6	1.63	101.9	1.4	1.45	103.6
6	1.4	1.37	97.9	0.6	0.59	98.3	1.5	1.52	101.3
7	0.6	0.62	103.3	0.8	0.83	103.7	1.5	1.51	100.7
8	1.1	1.10	100.0	1.8	1.79	99.4	0.8	0.81	101.6
9	1.9	1.94	102.1	1.6	1.62	101.3	1.3	1.28	98.5
10	2.0	2.03	101.5	1.9	1.85	97.4	1.5	1.52	101.3
RPE_s(%)	2.30			1.98			3.20		
RPE_T(%)	2.50								

[a] Recovery.

Table 4. Estimated and Actual Concentrations of 4-Nitrophenol, 2,4-Dinitrophenol, and 2,4,6-Trinitrophenol in Synthetic Mixtures (Validation Set) by Optimized PC-ANN Model

	concentration (mmol L^{-1})								
	4-Nph			4-Nph			2,4,6-triNph		
sample number (prediction set)	actual	found	rec. (%)[a]	actual	found	rec. (%)	actual	found	rec. (%)
1	1.6	1.56	97.5	1.0	1.05	105.0	1.4	1.38	98.6
2	1.8	1.82	101.1	0.8	0.84	105.0	0.9	0.92	102.2
3	1.3	1.38	106.2	1.8	1.79	99.4	0.6	0.66	110.0
4	1.8	1.74	96.7	1.6	1.54	96.3	1.4	1.4	100.0
5	1.3	1.36	104.6	1.9	1.84	96.8	1.5	1.46	97.3
6	0.6	0.59	98.3	1.3	1.39	106.9	1.6	1.52	95.0
7	0.6	0.74	123.3	1.4	1.46	104.3	1.4	1.4	100.0
8	1.1	1.15	104.5	1.7	1.79	105.3	0.6	0.58	96.7
9	1.9	2.06	108.4	1.9	1.94	102.1	1.9	2.06	108.4
10	1.9	1.95	102.6	1.4	1.33	95.0	1.3	1.32	101.5
RPE_s(%)	5.53			4.03			4.71		
RPE_T(%)	4.78								

[a] Recovery.

Evolution of the Performance of the Best Artificial Neural Network for Prediction of Nitrophenols in Synthetic Mixtures. To evaluate the performance of the proposed method for the simultaneous determination of 4-nitrophenol, 2,4-dinitrophenol, and 2,4,6-trinitrophenol in mixture samples, the optimized neural network models were tested on a prediction set and validation set that consisted of samples belonging to neither the calibration set nor the prediction set.

The results are summarized in Tables 3 and 4. As can be seen, there were good and reasonable agreements between

Table 5. Comparison of Different Methods That Were Used for Determination of Some Nitrophenols

analyte	method	matrix	recovery (%)	concentration range	reference
4-nitrophenol	electrochemical immunoassay	clinical serum	89.6−110.6	8.0×10^{-7} to 2.0×10^{2} ng/mL	64
4-nitrophenol	voltammetric sensor	water	99.4−100.4	0.0011−0.695 μg mL^{-1}	65
3-nitrophenol	capillary electrophoresis	water	91.8−109.1	0.348−3.48 μg mL^{-1}	66
4-nitrophenol	derivative voltammetry	water	96.0−102.0	0.278−556.44 μg mL^{-1}	67
3-nitrophenol			97.0−101.0	1.39−139.11 μg mL^{-1}	
2-nitrophenol			98.0−101.7	0.556−139.11 μg mL^{-1}	
2-nitrophenol	reflectometry	water	95−124	0.002−0.556 μg mL^{-1}	68
4-nitrophenol			104−119	0.00097−0.083 μg mL^{-1}	
2,4-dinitrophenol			92−111	0.0009−0.147 μg mL^{-1}	
4-nitrophenol	spectrophotometry−PLS	water	84−122.3	1.0−10.0 μg mL^{-1}	69
3-nitrophenol			83.5−115.0	1.0−20.0 μg mL^{-1}	
2-nitrophenol			89.0−111.6	1.0−20.0 μg mL^{-1}	
4-nitrophenol	spectrophotometry−LS-SVM	water	96.9−105.8	1.92−4.00 μg mL^{-1}	70
2-nitrophenol			97.7−102.3	9.60−19.20 μg mL^{-1}	
2,4-dinitrophenol			93.1−102.1	2.88−6.00 μg mL^{-1}	
4-nitrophenol	conductometry acid−base titration−ANN	water	96.9−103.3	0.6−1.9 μg mL^{-1}	present work
2,4-dinitrophenol			97.1−103.7	0.8−1.9 μg mL^{-1}	
2,4,6-trinitrophenol			93.3−105.8	0.6−1.9 μg mL^{-1}	

the obtained and real concentrations of the prediction and validation samples.

The low RPET (eq 8) and RPEs (eq 9) values were obtained (<6%, Table 3), and the recoveries (eq 10) were also satisfactory.

These results indicate that the networks used can properly process the titration data and model the complex relationship between the concentration of nitrophenols in the mixture and conductance data at different volumes of the titrant.

So, the proposed method can be successfully applied in simultaneous analysis of 4-nitrophenol, 2,4-dinitrophenol, and 2,4,6-trinitrophenol in mixture samples.

CONCLUSION

4-Nitrophenol, 2,4-dinitrophenol, and 2,4,6-trinitrophenol mixture is an extremely difficult complex system due to overlapping observed among the conductometric titration data. To overcome the drawback of this interference, a principal component artifical neural network calibration model was proposed for the simultaneous determination of mixtures of nitrophenols, using the conductometric titration method. This modeling could process the nonlinear relationship between the conductances of solutions at a given volume of titrant and concentration of nitrophenols and predict the concentration of them in an unknown sample.

The good agreement between the calculated and experimental concentrations of the three components, the low RPE_T and RPE_s obtained values (<6%), and the satisfactory resulted recoveries clearly demonstrates successful application of this procedure for the simultaneous determination of 4-nitrophenol, 2,4-dinitrophenol, and 2,4,6-trinitrophenol. In addition, the method was compared to some previous works for the determination of some of the nitrophenols in water samples (see Table 5). As can be seen, the results are comparable in quality to others obtained by some analytical methodologies[64−68] and by other chemometric methods such as partial least-squares (PLS)[69] and least-squares support vector machines (LS-SVM).[70]

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ACKNOWLEDGMENT

We gratefully acknowledge the financial support of this work by Ferdowsi University of Mashhad.

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