

ANFIS Based Prediction of the Percentage of Lanthanum Extraction Obtained Using Solvent Extraction Technique

Sagarika Acharya¹, Sunita Chand² and Sujata Mishra^{1*}

¹Department of Chemistry, Institute of Technical Education and Research, Siksha 'O' Anusandhan University, Bhubaneswar, Odisha, India. ²Centre for Applied Mathematics & Computing Institute of Technical Education and Research, Siksha

²Centre for Applied Mathematics& Computing, Institute of Technical Education and Research, Siksha 'O' Anusandhan University, Bhubaneswar, Odisha, India.

*Corresponding Author: sujatamishra@soa.ac.in

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I. INTRODUCTION

The solvent extraction as a separation technique is widely used because of its advantages such as ease, quickness, better metal recovery, high product purity and applicability both at lab and commercial scale [1]. The partition of the rare earth elements is quite difficult as they resemble in their chemical characteristics.Increasing requirements have prompted the investigators to come up with processes for the effective separation of these metals from diverse resources. Owing to their distinctive properties these have been extensively useful as magnetic,optical,catalytic and fluorescent materials [2]. Lanthanum is one of the rare earth elements abundantly present in monazite [3]. Thermodynamic equilibrium data modelling on solving a number of nonlinear equilibrium equations simultaneously in case of solvent extraction of rare earths with saponified PC 88A using artificial neural network

Abstract:

The solvent extraction process needs to be optimized by metal feed concentration, extractant and salt concentrations. The modeling of extraction equilibrium data provides valuable insight to the feasibility of the process through optimization. The chemical models need determination of chemical reaction among various entities of the system while the mathematical models finds it difficult to enhance the prediction range beyond a certain limit.Computer modeling like ANFIS can give a better and accurateprediction without prior knowledge of chemical stoichiometry. In this present study ANFIS(Adaptive Neuro Fuzzy Inference System) has been adopted for a solvent extraction system involving La(III) with acidic and basic extractants from various aqueous media. The conditions for least average error have been reported.

has been reported by Giles et al.[4]. In the recent times, the intelligent systemadvances have achieved increasing attractiveness in varioussectors of engineering for modeling andsimulation of environmental problems. Kemper, Sommer [5] have evaluated the metalconcentrations in soils employingback propagationnetwork and multiple linear regression. The present paper focuses on the design of an ANFIS (Adaptive Neuro Fuzzy System)model Inference by considering the operating parameters as inputs and percentage of extraction of La (III) as output for La-DEHPA, La-PC 88A and La-Aliquat 336 solvent extraction systems.

The extraction percentage of lanthanum (III) has been determined using variable operating conditions. The organic extractants used here are organophosphorus acids (DEHPA and PC 88A) and Aliquat 336.The extraction experiments have been



performed with variations in shaking time, temperature, pH or acid molarity, concentrations of La(III),extractant,NaNO₃(in case of La-Aliquat336) andO/A phase volume ratio.

II. Methodology

ANFIS is a soft computing method in which the input and output data are expressed in a fuzzy environment. ANFIS is used preferably when the data set is small, whereas ANN (Artificial Neural Network) is used for larger data sets. Furthermore, compared to ANN, ANFIS is more transparent to the user and minimizes the error as it has both numerical and linguistic knowledge. The objective of a neurofuzzy system is to use neural learning techniques to recognize the factors and/or architecture of neurofuzzy systems. These systems can unite the advantages of the two controlling patterns into a single case. These comprise rapid and precise learning, good simplification capabilities, exceptional clarification facilities in terms of significant fuzzy rules, and the capacity to hold both data and existing expert understanding concerning the problem under consideration. The aim of ANFISis to obtain a model or mapping that will properly connect the inputs with the target.Unlike ANN, ANFIS system doesn't have a defined method of guidance and takes a long time for adjustment of the membership functions.Neural Networks are characterized by three components i.e., nodes, weights and the activation or transfer function. Neural network consisting of three layerscalculates the v(output) from the xi, i=1... n (inputs). A transferfunctionf is associated with all neurons. In fuzzy neural nets, a few or the entire number of inputs xi, weight function wijmultiplied to each input and the shift term hiinvolved are fuzzy. Inthe present ANFIS model the back propagation learning rule with the sigmoidal function has been chosen as activation function. Three fuzzy (IF...THEN...) rules with membership function mf1 which is sigmoidal in nature have been considered and mathematically it is defined as

Where manages the slope at the crossover point . Th back propagation technique is a commonly used technique in neural networks, where the gradient vector is computed in the opposite direction to the output and after it is found, regression techniques are used for updating the parameters.

III. Results and discussion

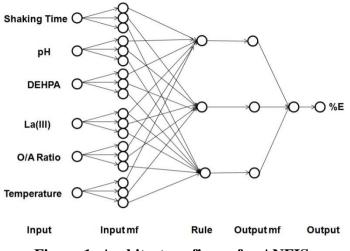
(i)DEHPA (di-2-ethylhexyl phosphoric acid) as extractant

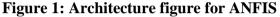
Table.1 lists the sets of data taken for train and test where (IF. THEN.) rule has been applied which is sigmoid in nature. The minimum testing error was 4.0 with 89% data used for training and 11% data for testing. Thestructural design figure for ANFIS has been displayed in Figure 1.

Table.1: Training and testing errors when rules are mf1 for all and sigmoid membership function

Input Data		Error	
Training	Testing	Training	Testing
25	11	76.1	13.6
26	10	76.2	11.4
27	9	76.1	10.8
28	8	75.7	11.0
29	7	75.1	11.8
30	6	75.1	12.5
31	5	75.1	9.5
32	4	74.3	6.5
33	3	74.0	4.0







(ii) PC88A(2-ethylhexyl phosphonic acid mono-2ethylhexyl ester) as extractant

The data sets were trained and tested using neuro fuzzy designer of MATLAB version 8.5.0. The sets of data when 70% trained and 30% tested the testing error was 20.6, whereas when the data sets were 86% tested and 4% trained the testing error obtained was 17.3. The training and testing errors obtained for various data sets has been given in Table 2 and the architecture figure for ANFIS has been given in Figure 2.

Table. 2: Training and testing errors when rules are mf1 for all and sigmoid membership function

Input Data		Error		
Training	Testing	Training	Testing	
21	9	44.2	20.6	
22	8	44.7	21.5	
23	7	44.7	20.6	
24	6	48.1	16.3	
25	5	48.7	16.2	
26	4	49.0	17.3	

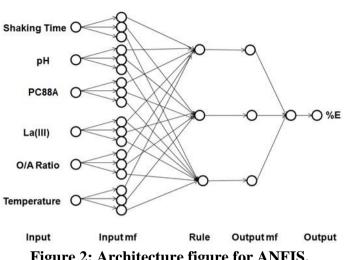


Figure 2: Architecture figure for ANFIS.

(iii)[A336][NO₃⁻](tricapryl methyl ammonium chloride) as extractant

Various sets of data were trained and tested respectively starting from 70% of data trained and 30% data tested up to 90% trained and 10% tested. The least average testing error has been obtained to be 5.78 with 70% data trained and 30% tested where the learning rule used is back propagation and sigmoid function. The training and testing errors were given in Table 3 and architecture for ANFIS in Figure 3.

Table 3: Training and testing errors when rulesare mf1 for all and sigmoid membership function

Input Data		Error	
Training	Testing	Training	Testing
20	9	46.0	27.2
21	8	48.3	22.0
22	7	50.3	22.0
23	6	50.3	18.5
24	5	51.5	15.6
25	4	52.5	9.74
26	3	53.12	5.7



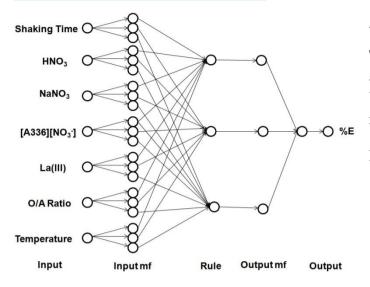


Figure 3: Architecture figure for ANFIS

Conclusions

Differentdata sets have been chosen for training and testing and the least average error in each case was determined. The average testing error minimizes on taking larger data sets. It was observed that the performance of the ANFIS model, with respect to the percentage extraction of lanthanum(III), was considerably influenced by variations in the shaking time,temperature,O/A phase volume ratio, pH/acid molarity, concentrations of La(III), extractant and NaNO₃(in case of La-Aliquat336). This model can be applied to design new systems for La(III) extraction and separation and also to optimizeprocess parameters for the existing solvent extraction systems. The demonstration of La (III) solvent extraction with ANFIS can be improved by incorporating several learning rules, activation functions. This can be extended for systems under variable experimental conditions and also in case of multi rare earths extraction and separation studies. It can have a considerable impact on the accuracy of extraction models based on speciation involved in chemical equilibriumdescribing process of solvent extraction.

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