A Multi-Layer Perceptron Used for Crude Oil Oxidation Prediction

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ABSTRACT

In-situ combustion (ISC) process is an important thermal enhanced oil recovery method. This process has a high considerable potential to enhanced oil recovery of heavy oil reservoirs. Crude oil oxidation is performed during ISC and plays a significant role in ISC performance. Thermogravimetric analysis is a technique to investigate crude oil oxidation. In this paper crude oil oxidation is predicted by multi-layer perceptron (MLP) neural network with two hidden layers, using data obtained from thermogravimetric analysis and separation experiments on six samples of Iranian heavy crude oil. We achieved the optimum network architecture and parameters by trial and error technique. The results of this study show that using an MLP including two hidden layers, we can predict the remaining crude oil mass in oxidation process versus time with an average absolute relative error (ARE) of 3.56 percent and a mean square error (MSE) 2.36. Moreover, the results of regression analysis showed that the predictions of the proposed neural network had an acceptable coincidence with experimental results.

Keywords

Thermogravimetric analysis, Artificial Neural network, multi-layer perceptron, MATLAB.

1. INTRODUCTION

In-situ combustion is a technique for enhanced oil recovery. In this method heat energy is generated within the reservoir by combustion front. Simultaneous air (oxygen) is injected to the reservoir in dry method and sometimes both water and air are injected (wet process). The necessary fuel for combustion front is supplied by the remaining reservoir oil (Cock), which is produced by distillation, thermal cracking and pyrolysis of the oil. During in-situ combustion, chemical and physical interactions are performed on crude oil such as distillation, thermal cracking, pyrolysis and oxidation. Effective mechanisms of enhanced oil recovery in this method are decreasing viscosity due to heating, dissolving of produced gas in oil, evaporation of light fractions and thermal cracking [1-3]. The propagation of combustion front and necessary air are controlled by exothermic oxidation interactions. Moreover, heat maximum, that is released, depends on oxidation and combustion interactions. Hence, the knowledge of these interactions is a necessary step for studying of in-situ combustion in porous media [4]. Based on thermal analysis method, one can recognize the chemical and physical displacements of a crude oil under oxidation conditions. Thermogravimetric analysis is recording weight changes continually when a sample is heating with constant rate. In recent years, the ability of an artificial neural network in learning with the use of experiences, and then capability of the generalization to solve a new problem, causes increasing in the use of this procedure in engineering. One of the powerful artificial neural network architectures, which has the best performance, is multi-layer perceptron (MLP) [5]. Necessary data for training and test include two portions, which are specification of crude oils (fractional weight of asphaltene, resin, dispersion, ˚API and viscosity) and results of thermogravimetric analysis.

2. ARTIFICIAL NEURAL NETWORKS

Recently Artificial Intelligence has been applied to help engineers to solve some problems in their fields. Artificial Neural network is a way to find relation between several varieties that there is not a mathematic relation for them. Artificial neural network is based on human neural system [6]. Artificial Neural networks have been trained to perform complex functions in various fields and play an important role as intelligence system. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. [7]. First artificial network must be a train. Therefore, data is divided into two portions called training and test. The training data is used to create the desired network. For adjusting of the weights, network output is compared with the desired output (target) in the training set, until the network output matches the target (supervised training). Finally after training, for validity the network test data was used to validation.

A neuron with an input vector is shown in Figure 1. Here the individual element inputs (p1, p2,... pR) are multiplied by weights (w1,1,w1,2,... w1,R) and the weighted values are fed

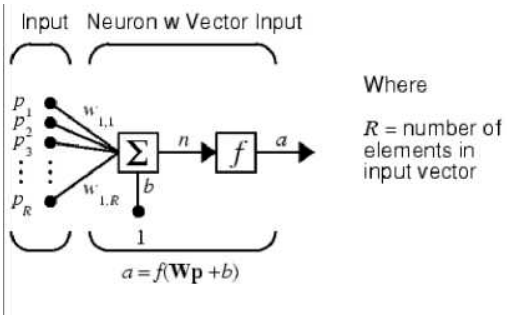

Fig 1. A neuron with an input vector

to the summing junction. Their sum is simply Wp, the dot product of the (single row) matrix W and the vector p.

The neuron has a bias b, which is summed with the weighted input to form the net input n. This sum, $n = \Sigma w_{1,i}p_i + b$, is the argument of the transfer function f. Many transfer functions are used in ANNs. Three of the most commonly used functions are tangent hyperbolic, logistic sigmoid and linear transfer functions, which are given by the equations 1-3, respectively:

$$a = f(n) = \frac{1 - e^{-2n}}{1 + e^{-2n}} \quad (1)$$

$$a = f(n) = \frac{1}{1 + \exp(-kn)} \quad (2)$$

$$a = f(n) = n \quad (3)$$

In which n is:

$$n = W * P + b \quad (4)$$

In the above equations, a, P, W, b and k are output of neuron, input vector, weight vector, bias and a constant parameter, respectively [7-9].

In this study, feed forward structures along with back propagation learning method are used in a multi-layer perceptron. The MLP consists of three layers called an input layer, a hidden layer (consisting of several layers) and an output layer. Neurons number of hidden layers and other neurons for each layer is very important in network performance [5, 10]. Unfortunately, there is not a confident way to find neurons number; in this study, trial and error were used to find the number of neurons.

When an ANN is created, small values are assigned randomly to the connections (weights) between neurons. In general, the output from neuron j in layer k can be calculated by the equation 5 [11,12]:

$$a_j^k = f^k(\sum_{i=1}^{N_{k-1}} w_{ij}^k a_i^{k-1} + b_j^k \quad (5)$$

The a_j^k is the output from neuron j in layer k, b_j^k is the bias weight of neuron j in layer k. The coefficients w_{ij}^k in the summations are the connection weights between neuron j in layer k and neuron i in layer k-1. The connection weights are the model fitting parameters. f^k is a symbol of transfer function in layer k [7].

3. EXPERIMENTS

Thermogravimetric analysis (TGA): the TGA experiments are performed. TGA is used to oxidize six samples of Iranian heavy crude oil. These experiments were performed on six samples of size ~ 30 mg, at 1 $^{\circ C}/_{min}$ heating rate. Air flow rate was kept constant at 50 $^{ml}/_{min}$ in the temperature range of 30-800 ℃.

Separation experiments: asphaltene, resin and dispersion fraction of crude oils are obtained by using ASTM D2007-80 method. Results of separation experiments and other crude oils specifications were listed in Table 1.

Table1. Specification of used crude oils

sample	1	2	3	4	5	6
API	20.83	21.87	18.67	20.26	13	30.39
Viscosity (cp)	157.3	117.9	306.5	185.87	3345.57	18.85
Resins (wt %)	8.09	6.01	13.73	14.04	16.42	4.01
Asphalten (wt %)	4.73	5.42	10.71	9.66	18.95	3.25
Dispersan t (wt %)	87.18	88.57	75.56	76.30	64.63	92.74

4. THE PROPOSED MLP MODEL

Oils specifications (physical properties and chemical component) and temperature were input to the network and the oil residual percent of six samples in different temperatures (thermogravimetric analysis) were set as an output. A set data was chosen randomly (30% of available data) as test set is used for validity. With trial and error technique, we find the optimum architecture of the network. Optimum network runs ten times and averages of results are considered as a final response of the network. At last, the best network was chosen based on calculating of error according to equations 5 and 6.

$$ARE = \frac{1}{n}\sum_{i=1}^{n}[\frac{|t(i) - a(i)|}{t(i)}] \quad (5)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(t(i) - a(i))^2 \quad (6)$$

where t and a are target and predicted outputs, respectively, and n is the number of used data for network training or testing.

4.1. Results and discussion

Here it is described how to find the optimum design architecture of the network, the best transfer function and training algorithm and finally the best MLP for the prediction of crude oil oxidation.

A. Determining the optimum number of neurons of the first hidden layer

As observed in Figure 3, the least ARE was occurred in a network which composed one hidden layer and containing 23 for training and testing set.

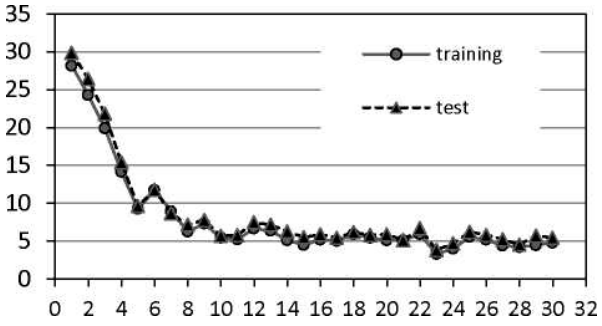

Fig 2. ARE versus the neurons number of the first hidden layer

B. Determining the optimum number of neurons of the second hidden layer

For the second hidden layer, an MLP was considered with two hidden layers with 23 neurons in first and the neurons number for second hidden layer, set from 1 to 20. As it is shown in Figure 3, the least ARE is a network with 8 neurons in the second hidden layer.

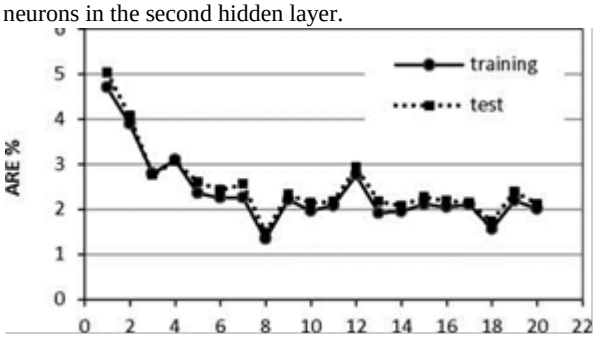

Fig 3. The network ARE versus the neurons number of the second hidden layer

C. Determining the optimum number of the hidden layers and their transfer functions

To finding the best network and the least error, several networks with one, two and three hidden layers and tangent hyperbolic, log sigmoid transfer function were designed. Then a multi-layer perceptron with two hidden layers and hyperbolic transfer function, after 10 runs has the best prediction.

D. Determining the best training algorithm

To find the best learning algorithm, the back propagation method with GDX, SCG, CGP, OSS, BFG and LM learning algorithm are used in feed forward, as well as two hidden layer networks with neuron number 23 , 8 for first and second hidden layers, respectively.

The ARE for various algorithm training versus the number of epochs are shown in Figure 4. As it is shown in Figure 4, using the SCG training algorithm, the least error occurred.

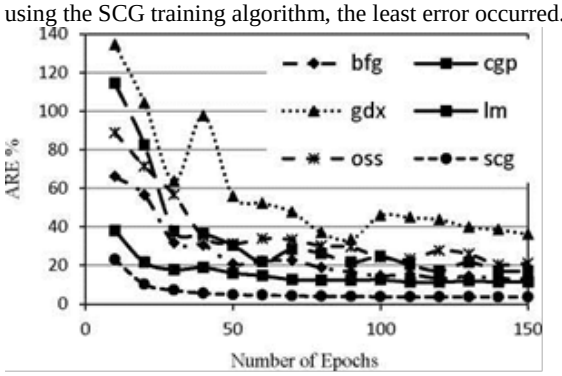

Fig 4. Determination of the best training function

E. The Optimum Network

Finally the optimum MLP was obtained based on the trial and error technique with the following characteristics for modeling and prediction of crude oil oxidation.

- ☐ MLP (2 hidden layers)
- ☐ tangent hyperbolic transfer function as a hidden layers transfer function
- ☐ linear transfer function as an output layer transfer function
- ☐ 23 neurons for first and 8 neurons for second hidden layers
- ☐ (SCG) algorithm as a network training algorithm

Fig. 5 shows error for 150 epochs. As it is shown, the ARE was less than 4% for training and testing set. Also Fig. 6 shows the ability of the proposed neural network for prediction of crude oil oxidation process.

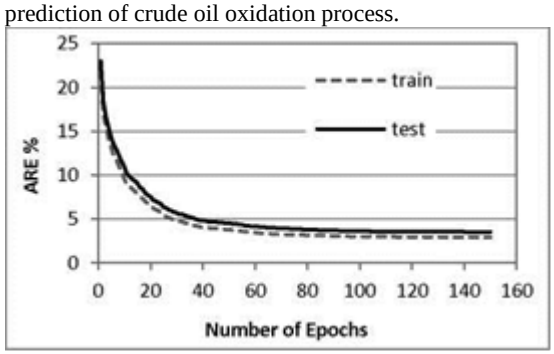

Fig 5. Calculated error for prediction of Crude oil oxidation process

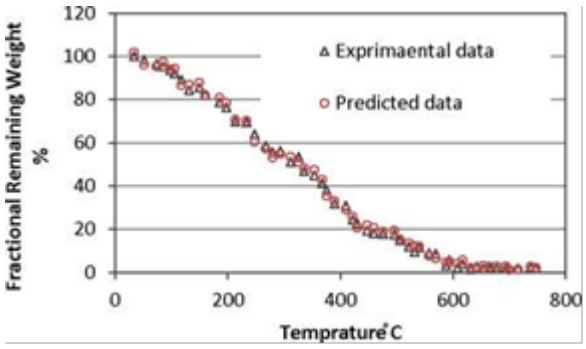

Fig 6. Experimental data and predicted data

ARE and MSE of each run are different with another run. Minimum, maximum and mean values of network ARE and MSE after 10 runs are shown in Table 2.

The regression analysis of the simulation of crude oil oxidation for test set data are:

Y=X+0.0011

Slope=1

Y-intercept =0.0011

Correlation Coefficient =0.999

Table 2. Network errors

Data set	Training Data	Testing Data
Minimum of network ARE (%)	0.98	3.53
Maximum of network ARE (%)	22.02	23.1
Mean of network ARE (%)	4.41	5.16
Minimum of network MSE	0.2	0.98
Maximum of network MSE	2.98	6.75
Mean of network MSE	1.23	2.36

Regression analysis results show, there exists a good coincidence between the experimental results and the predicted results by the proposed network.

With regard to Figure 8, the following values were obtained as outputs of postreg function:

Slope=1

Y-intercept =0.0011

Correlation Coefficient =0.999

Regression analysis results show, there exists a good coincidence between the experimental results and the predicted results by the proposed network.

5. CONCLUSION

Obtained results of this research are shown that (MLP), as Artificial Intelligence, is capable for prediction of crude oil oxidation. Therefore, artificial neural networks can be used to modelling and prediction of many engineering works. Also we achieved to the best architecture, transfer function, training algorithm and number of neurons for each hidden layers by trial and error technique. API density, viscosity, resin and asphaltene and other components of crude oil percentage, temperature were network input parameters and residual weight percentage in different temperatures was network output.

6. ACKNOWLEDGEMENT

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REFERENCES

[1] Green, D.W. and Willhite, G.P. Enhanced Oil Recovery, Textbook Series SPE, Richardson, Texas (1998).

[2] Van pollen, H.K. et. al. Fundamental of Enhanced Oil Recovery, PennWell Publishing Company, Oklahoma, 1980.

[3] Ramey, H.J. Thermal Methods of Oil Recovery, Gulf Publishing Company, Texas (1985).

[4] J.G.BURGER, B. C. SAHUQUET. "Chemical Aspect of In-situ Combustion - Heat of Combustion and Kinetics " SPE Paper 3599 , presented at SPE 46th Annual Fall Meeting, held in New Orleans, Oct. 3-6, 1971.

[5] Picton,Ph. "Neural Network," Second Edition, Publishing by PALGRAVE, New York (2000).

[6] Mohaghegh, S., Arefi, R., Ameri, S.,“ A Methodological Approach For Reservoir Heterogeneity Characterization Using Artifacial Neural Networks," SPE 28394, (1994).

[7] Demuth, H. and Beale, M. ”Neural Network Toolbox for Use with Matlab,” Fifth Edition, Mathworks(1998).

[8] Beale, R. and Jackson, T. "Neural Computing: An Introduction ," IOP Publishing, Bristok, UK(1998).
[9] Shulkoff, R.J. "Artificial Neural Network," Mc Graw-Hik, New York (1997).
[10] Dayhoff J.E., Neural Network Architectures, Van Nostrand Reinhold, New York, 1990.
[11] Gharbi, R., 1997. Estimating the isothermal compressibility coefficient of under saturated Middle East crudes using neural networks, Energy & Fuels, 11: 372-37 8.
[12] Moghadassi, A. and et. Al. " A New Approach Based on Artificial Neural Networks for Prediction of HighPressure Vapor liquid Equilibrium," Australian Journal of Basic and Applied Sciences, 3(3): 1851-1862, 2009.