

## Generalized net model of the process of defining intuitionistic fuzzy estimation in petroleum recognition with neural networks

Sotir Sotirov and Alexander Dimitrov

University “Prof. Asen Zlatarov”  
1 “Yakimov” Blvd., Burgas 8010, Bulgaria  
e-mails: ssotirov@btu.bg, al\_dim\_2000@abv.bg

**Abstract:** The paper presents a neural network that performs clustering and recognition of petroleum fractions. For the purpose of practical implementation, the degrees of petroleum probes’ affiliation to the clusters are measured using intuitionistic fuzzy estimations. The entire process of petroleum identification is modelled using a generalized net.

**Keywords:** Generalized nets, Intuitionistic fuzzy sets, Neural networks, Petroleum fraction.

**AMS Classification:** 03E72, 68Q85, 92B20.

### 1 Introduction

Rational utilization of petroleum is related to knowledge about its chemical composition which is the main factor when choosing the proper method of processing and determines to a great extent the quality of the fuels and lubricants produced [7].

Petroleum fractions are multicomponent mixtures of hydrocarbons of different homologous series including small amounts of sulfur-, nitrogen- and oxygen-containing compounds. By identifying the individual hydrocarbon and heteroatomic components, the specific hydrocarbon composition and heteroatomic compounds can be determined. This task, however, is quite labour consuming and it can not be fully accomplished yet for the high-boiling petroleum fractions. Besides, the full information about petroleum composition is not necessary in most cases. Thus, the elemental, group and structural group compositions of the petroleum fractions are usually determined.

All the analytical methods are easier to use and the results obtained are more reliable when the composition of the petroleum product studied is simpler. Therefore, before stepping into the analysis, petroleum should be separated into fractions. The fractions are usually separated further to different hydrocarbon groups by physical methods and these groups are analyzed. In other cases, the contents of some elements like sulfur, nitrogen, etc., or groups of compounds like solid paraffins, resins, asphaltenes, etc. are determined.

The average boiling temperatures are determined with substantial precision only for the petroleum fractions boiling in narrow temperature interval. For fractions boiling in wide temperature interval, the percentages distillate obtained at certain temperatures are established. The combination of data on the percent distillate obtained at different temperatures is called fractional composition.

The aim of the present paper is to use the techniques of neural networks [2, 3, 4, 5, 6] to give

a estimation of the degree of recognition in intuitionistic fuzzy sets [1]. The paper based on [8].

The  $m$  parameters of the different individual fractions enter the inputs of the neural network. The evaluation is formed on the basis of these parameters.

These assessments, which estimate the degree of the affiliations ( $\mu$ ) and the non-affiliations ( $\nu$ ) of the information obtained, are represented by ordered pairs  $\langle \mu, \nu \rangle$  of real numbers from the set  $[0; 1] \times [0; 1]$ .

The degree of uncertainty  $\pi = 1 - \mu - \nu$  represents those cases where the neural network can not answer the question and needs additional information. Everywhere the ordered pairs have been defined in the sense of intuitionistic fuzzy sets.

## 2 Neural network

In [2, 3, 4], different types of neural networks are described. Many of them are used for image recognition (symbols, classes, knowledge, etc). Neural networks can be used for obtaining intuitionistic fuzzy evaluation, [1]. In the present paper, we use a feed-forward neural network with structure, as illustrated in Fig.1.

On the inputs  $x_1, \dots, x_m$  of the neural network there are petroleum parameters of the different individual fraction.

Outputs  $a_\mu, a_\nu$  and  $a_\pi$  obtain intuitionistic fuzzy evaluations. The first output gives the degree of affiliation of the current petroleum probe to the respective petroleum cluster –  $\mu$ ; the second – degree of non-affiliation of the current petroleum probe to the respective petroleum cluster –  $\nu$ , and the third – degree of uncertainty  $\pi = 1 - \mu - \nu$ .

The next three outputs obtain number of the petroleum.

For the realization of our purpose a two-layer feed-forward neural network is used. The  $P_{17 \times 1}$  vector is fed at the input, and the  $T_{6 \times 1}$  is produced at the output. The input layer consists of 8 neurons, as the standard logic function (logsig) is used as a transfer function.

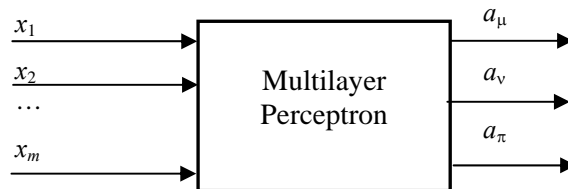


Figure 1. Nodes of the Multilayer Perceptron

The network learning is performed in MATLAB environment by means of the Levenberg-Marquardt algorithm with a set mean square error of  $1.10^{-5}$ .

At the beginning, a statistical analysis of the 17 parameters is done on the three different sort of petroleum, and after that the neural network is learned. Initially, when no information has been obtained yet, all estimations are given initial values of  $\langle 0, 0 \rangle$ . When  $k \geq 0$ , the current  $(k+1)^{\text{st}}$  estimation is calculated on the basis of the previous estimations according to the recurrence relation

$$\langle \mu_{k+1}, \nu_{k+1} \rangle = \left\langle \frac{\mu_k k + m}{k+1}, \frac{\nu_k k + n}{k+1} \right\rangle,$$

where  $\langle \mu_k, \nu_k \rangle$  is the previous estimation, and  $\langle \mu, \nu \rangle$  is the estimation of the latest measurement for  $m, n \in [0; 1]$  and  $m + n \leq 1$ . These values are used for training the neural network (Fig. 1).

### 3 A GN-model

The constructed model is illustrated in Fig. 2. It is presented by a set of transitions:

$$A = \{Z_0, Z_1, Z_2, Z_3, Z_4\},$$

where transitions describe the following processes:

- $Z_0$  = Forming the input data;
- $Z_1$  = Selecting of MLP structure;
- $Z_2$  = Learning of the MLP;
- $Z_3$  = Data visualization;
- $Z_4$  = Testing of the results.

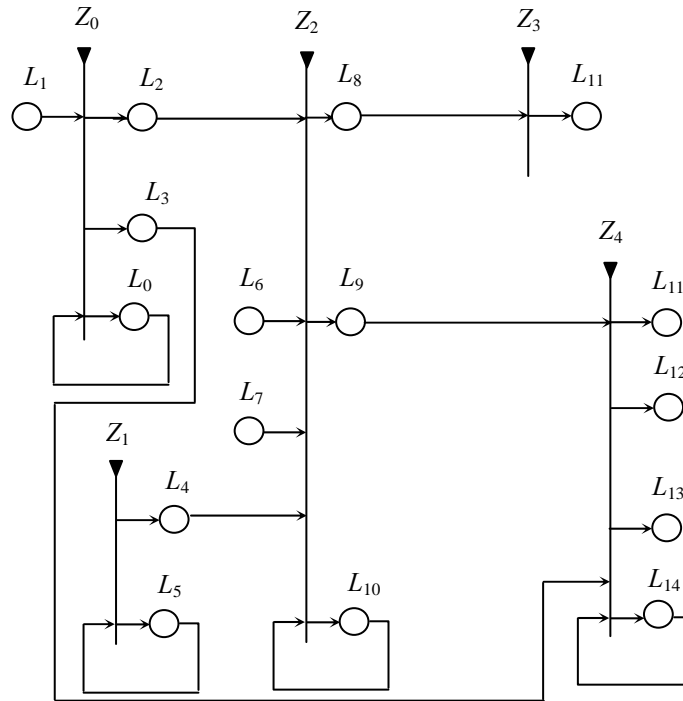


Figure 2. GN model of the recognition using the Multi Layer Perceptron

Initially, one token stays in place  $L_5$  and keeps staying there during the whole GN functioning. While it may split into two or more tokens, the original token will remain in its first place. The original token has the initial and current characteristic “Database with MLP structures”.

Also initially, the following tokens enter the GN:

- from place  $L_1$  – one token with initial characteristic “Petroleum parameters of the different individual fraction”;
- from place  $L_6$  – one token with initial characteristic “Number of iterations for learning of the MLP”;
- from place  $L_7$  – one token with initial characteristic “Preliminarily condition for learning”.

The transitions of the GN-model have the following forms.

$$Z_0 = \langle \{L_1, L_0\}, \{L_2, L_3, L_0\}, R_0, \vee(L_1, L_0) \rangle,$$

$$R_0 = \frac{\quad}{\begin{array}{l} L_1 \\ L_{15+n} \\ L_0 \end{array}} \left| \begin{array}{ccc} L_2 & L_3 & L_0 \\ \hline False & False & True \\ False & False & True \\ W_{0,2} & W_{0,3} & True \end{array} \right.,$$

where

$W_{0,2}$  = “The data are prepared”;

$W_{0,3} = \neg W_{0,2}$ .

The tokens that enter in places  $L_2$  and  $L_3$  obtain characteristics “Prepared data”.

$$Z_1 = \langle \{L_5\}, \{L_4, L_5\}, R_1 \rangle$$

$$R_1 = \frac{\quad}{L_5} \left| \begin{array}{cc} L_4 & L_5 \\ \hline True & W_{4,5} \end{array} \right.,$$

where:

$W_{4,5}$  = “The structure is chosen”.

Token that enters in place  $L_5$  obtain characteristic “Selected structure of the MLP”.

$$Z_2 = \langle \{L_2, L_6, L_7, L_4, L_{10}\}, \{L_8, L_9, L_{10}\}, R_2, \vee(L_2, L_6, L_7, L_4, L_{10}) \rangle$$

$$R_2 = \frac{\quad}{\begin{array}{l} L_2 \\ L_6 \\ L_7 \\ L_4 \\ L_{10} \end{array}} \left| \begin{array}{ccc} L_8 & L_9 & L_{10} \\ \hline False & False & True \\ False & False & True \\ False & False & True \\ False & False & True \\ W_{10,8} & W_{10,9} & True \end{array} \right.,$$

where:

$W_{10,8} = W_{10,9}$  = “The MLP is learned”.

The tokens that enter places  $L_8$  and  $L_9$  obtain characteristics “Learned MLP”.

$$Z_3 = \langle \{L_8\}, \{L_{11}\}, R_3 \rangle$$

$$R_3 = \frac{\quad}{L_8} \left| \begin{array}{c} L_{11} \\ \hline True \end{array} \right..$$

The token that enters place  $L_{11}$  obtains characteristic “Data visualization of the results of the MLP”.

$$Z_4 = \langle \{L_9, L_3, L_{14}\}, \{L_{11}, L_{12}, L_{13}, L_{14}\}, R_4, \wedge(L_9, L_3, L_{14}) \rangle$$

$$R_4 = \frac{\quad}{\begin{array}{l} L_9 \\ L_3 \\ L_{14} \end{array}} \left| \begin{array}{cccc} L_{11} & L_{12} & L_{13} & L_{14} \\ \hline False & False & False & True \\ False & False & False & True \\ W_{14,11} & W_{14,12} & W_{14,13} & True \end{array} \right.,$$

where:

$W_{14,11}$  = “There is a new value for the  $\mu$ ”;

$W_{14,12}$  = “There is a new value for the  $\nu$ ”;

$W_{14,13}$  = “There is a new value for the  $1 - \mu - \nu$ ”;

The tokens that enter places  $L_{11}$ ,  $L_{12}$  and  $L_{13}$  obtain characteristics, respectively: “ $\mu$ ”, “ $\nu$ ” and “ $\pi = 1 - \mu - \nu$ ”.

## Conclusion

The proposed generalized net model presents a neural network that determines the intuitionistic fuzzy degrees of affiliation, non-affiliation and uncertainty within the process of petroleum recognition and fractioning, based on a predefined set of criteria.

## References

- [1] Atanassov, K. *Intuitionistic Fuzzy Sets: Theory and Applications*, Springer, Heidelberg, 1999.
- [2] Bishop, C. M. *Neural Networks for Pattern Recognition*, Oxford University Press, 2000.
- [3] Haykin, S. *Neural Networks: A Comprehensive Foundation*, Prentice Hall, N.J., 1999.
- [4] Hagan, M.T., H.B. Demuth, M. Beale. *Neural Network Design*, PWS Publishing Company, Boston, 1996.
- [5] Barbosa, M.S.S., T. B. Ludermir, M. S. Santos, F. Luiz dos Santos, J. E. Gomes de Souza, C. Pinto de Melo, Pattern recognition of gases of petroleum based on RBF model, *Proc. of VII Brazilian Symposium on Neural Networks (SBRN'02)*, 2002, pp. 111.
- [6] Hsieh, B.-Z., C.-W. Wang, Z.-S. Lin, Estimation of formation strength index of aquifer from neural networks. *Computers & Geosciences*, Volume 35, Issue 9, September 2009, 1933–1939.
- [7] Speight, J. G. *Handbook of Petroleum Product Analysis* (Chemical Analysis: A Series of Monographs on Analytical Chemistry and Its Applications), Wiley-Interscience, October 2, 2002.
- [8] Sotirov, S., A. Dimitrov. Neural network for defining intuitionistic fuzzy estimation in petroleum recognition, *Issues in Intuitionistic Fuzzy Sets and Generalized Nets*, Volume 8, 2010, 74–78.