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Research Article

Estimation of the Bubble Point Pressure of Crude Oil Reservoir Using Adaptive Fuzzy Neural Network

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ABSTRACT

To develop the oil fields in various processes, such as Enhanced Oil Recovery, aware of the properties of the reservoir fluids is essential while the bubble pressure is one of those importances. Bubble point pressure is a critical pressure volume temperature property of reservoir fluid, that plays an important role in almost tasks involved reservoir and production engineering. The main objective of this study was to present a novel approach to access more accurate bubble point pressure of crude oils prediction model based on the combination of the field data using adaptive neural–fuzzy Inference system. It was obtained that there is a significant error between field data and predicted model which are 0.035033 and 0.088093 for Average Absolute Error and Average Absolute Deviation error, respectively. It may be concluded that the designed ANFIS model has well accurate and able to predict bubble point pressure of crude oils.

Key words: bubble point pressure, Adaptive neural–fuzzy Inference system, crude oil.

1. INTRODUCTION

For calculating the reserves in oil reservoir and its performance and other reservoir characteristics is required the accurate calculation of properties of the fluid's physical properties. To develop an oil field such as gas injection to Enhanced Oil Recovery (EOR), the set of properties of fluid reservoir is required that the most important of these properties are including Bubble point pressure, Gas Oil Ratio, and Oil Formation Volume Factor. The Bubble point pressure of a hydrocarbon system is defined as the maximum pressure at which a gas bubble is first free from the oil. This feature can be measured empirically for a crude oil system by a constant composition expansion (CCE) experiment. Also, the bubble point pressure is used, either directly or indirectly, almost all relationships need to predict the properties of crude oil. Therefore, the estimation error of bubble point pressure will have an effect estimates on other fluid properties such as oil formation volume factor, oil viscosity, oil density, etc. Therefore, it is absolutely necessary that the forecasts for bubble point pressure be as accurate as possible. Various graphical and mathematical equations to determine the bubble point pressure have been proposed during the past six decades [1-6]. Different relations by different researchers, with varying degrees of precision, based on samples of crude oil from various fields are presented. Most of these relationships focused on multiple regression techniques for e.g. Elsharkawy [7] or other non-parametric regression techniques such as the Alternating Conditional Expectation (ACE) algorithm or Genetic Programming. However, these presented models are not accurate enough to predict BPP in the oil industry. Most of them require complex and time consuming computations and also a lot of input information to achieve the answer.

Based on the above discussion, it is obvious that there is a research requirement for developing new models. These models should not have the limitations and complexities of the available models. In other words, the new models should be more accurate, robust and less sensitive to noisy input data, adaptive to a new input-output information and also should require the least amount of input information. Intelligent models, offer all of the above desirable characteristics. Intelligent systems have various kinds of fuzzy logic and neural networks are the most important. Several authors such as Al-Marhoun and Osman [8], El-Sebakhy et al. [9] Elsharkawy [10], Gharbi [11] and Osman et al. [12] have used various network architectures such as Multi-Layer Perception (MLP) or radial basis function network and various training and validation algorithms such as back propagation and support vector regression. Some of these models were optimized for better prediction of regional crudes, while some were constructed to be globally applicable. A new semi analytical model for prediction of bubble point pressure of crude oils has been developed and reported by literatures [13]. In this work, a semi-analytical model for prediction of bubble point pressure is proposed. The model uses temperature–concentration interaction terms to portray the fluid behavior. One of the most important and most effective intelligent systems composed of neural networks and fuzzy logic is ANFIS. Therefore, the main objective of this study was a novel approach using ANFIS for accurate improve predicting the bubble point pressure of crude oils.

2. Model Development

2.1. Adaptive Network–Based Fuzzy Inference System

A fuzzy inference system, a system based on fuzzy if–then rules that applying these rules, the ability to find any type or model is a nonlinear mapping, so that these models can be input with corresponding outputs relevant. The process of formulating the mapping from a given input to an output using fuzzy logic, fuzzy inference system is called. There are three useful fuzzy inference systems: namely the linguistic (Mamdani-type) [14-16], the relational equation and the Takagi–Sugeno–Kang (TSK) [17].

The main difference between these systems is the output, so that the Mamdani system, the output is a fuzzy set should be defuzzification but Sugeno system output is a linear or constant. On the other hand, neural network learning capability and can be using of train data, the network parameters are adjusted so that the desired input rate, the desired output is achieved.

However, neural networks, the use of human knowledge, in contrast, fuzzy systems cannot be used to derive linguistic expressions. So, to create a better learning ability and achieve more accurate approximations, combining the learning capabilities of neural networks and fuzzy systems infer properties of the TSK fuzzy model, called Adaptive Neural Fuzzy inference system (ANFIS) was presented in 1999 [18-20]. In other words, a fuzzy neural system is a fuzzy system that to determine its parameters used from training samples processed by the learning algorithm that derive or inspired by neural network theory. In Figure 1, for simplicity, a network with two inputs x, y and output f is considered.

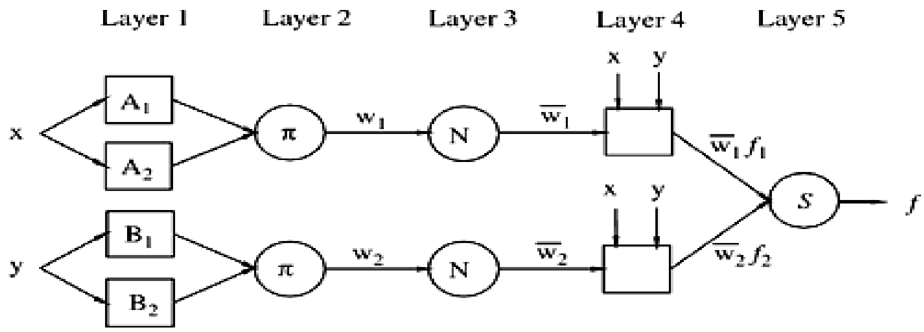

Fig. 1: Schematic of ANFIS architecture [21].

2.2. Neural - fuzzy Modeling

To develop ANFIS, model data set obtained from data set were used which collected from literatures (Table1). To develop an intelligent system, the most important physical skill required is to make a decision what the principal inputs and output(s) of the system are. In this study, the input parameters were concentration C1, concentration C7+ and temperature. The desirable output of the model was the Bubble Point Pressure (BPP). To achieve this goal, model ANFIS was designed. In ANFIS model, BPP was a function of concentration C1, concentration C7+ and temperature; therefore, the model has 3 and 1 input and output, respectively:

BPP = f_{ANFIS} (concentration C1, concentration C7 +, Temperature) (1)

The fuzzy BPP modeling system used in this study is a multi-input single output (MISO) Takagi-Sugeno system. First, available data divided into two parts of training and testing data. Because of large number of input variables, scatter partitioning was used to avoid “curse of dimensionality” problem instead of grid partitioning. The ANFIS model was designed to prediction of bubble point pressure of crude oils. To develop this model data set (Table 1) was used. Table 2 shows the details of optimal fuzzy model designed for ANFIS model. The best parameters of obtained fuzzy clustering designed for ANFIS model is shown in Table 3. This arrangement resulted by trial and error procedure. Hybrid optimization method was used to optimize generated fuzzy inference system (FIS) and the best model was selected according to minimum absolute relative deviation (AAPE) and average absolute deviation (TAAD). These errors are defined as follows:

$$\mathrm{TAAD\%} = \frac{100}{N} \times \left| \frac{\sum_{i=1}^{N}\left(y_i^{exp} - y_i^{cal}\right)}{y_i^{exp}} \right|$$

$$\mathrm{AAPE\%} = \frac{100}{N} \left| \sum_{i=1}^{N}\left(y_i^{exp} - y_i^{cal}\right) \right|$$

Where y_i^{exp} and y_i^{cal} are target and model output for the ith output, and N is the total number of events considered.

Table 1: Ranges of the input variables used in developing the ANFIS model.

Parameter	Minimum	Maximum
C1(mole fraction)	5.63	74.18
C7+(mole fraction)	3.61	83.2
Temp.(F)	128	314

Table 2: Characteristics of fuzzy model for ANFIS

Parameter	Operator
AND	prod
OR	probor
Implication	prod
Aggregation	max
Difuzzification	wtaver

Table 3: The best parameters set parameters for the ANFIS.

Parameter	Value
Range of influence	0.64
Squash factor	1.25
Squash factor	0.5
Reject ratio	0.15

2.3. Selection of Training Data and Test

To developing a neural-fuzzy model, the first step is determining appropriate inputs and outputs for the system. The data required for designing and training the designed model was extracted from researches [13, 14] related to surveying the prediction of Bubble Point Pressure of Crude Oil Reservoir. The input parameters were concentration C1, concentration C7+ and temperature and desirable output of the model was the Bubble Point Pressure (BPP). The total number of used data was 159 where divided to two parts, network training data (86) and test data (43).

3. RESULTS AND DISCUSSION

Table 4 shows the features and functions of designed model compared with the actual results.

Table 4: Error analysis of different models

Model	ANFIS	Bandyopadhyay	Elsharkawy	SRK-EOS	PR-EOS
AAE%	3.5033%	7.83%	8.32%	10.15%	10.58%
AAD	145.5822 psi	158.8 psi	182.2 psi	209.2 psi	226.5 psi

Figures 2 shows the results of testing ANFIS model compared with experimental results in this study. In Figures 3, actual results against output for ANFIS model are shown.

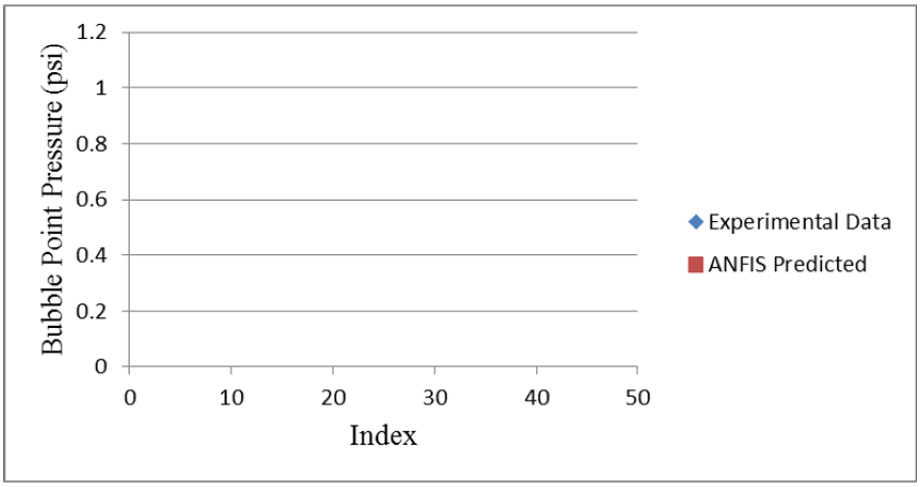

Fig. 2: Experimental results against output for ANFIS model.

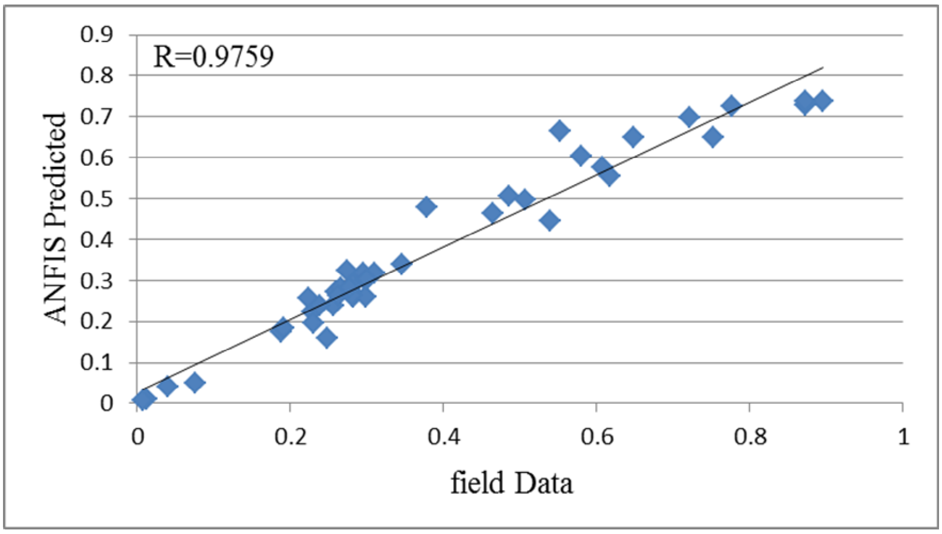

Fig. 3: Experimental data versus ANFIS model outputs.

The output surface built is shown in Figure 4. The first and second inputs in the figures are concentration of C1 and C7+, respectively.

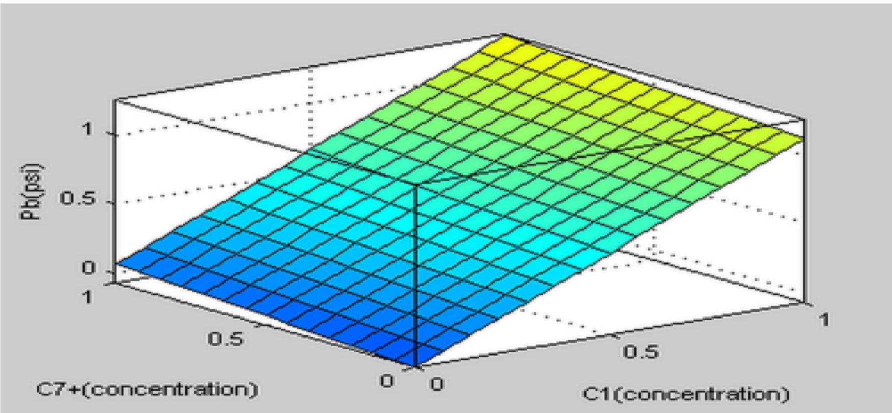

Fig. 4. ANFIS-generated surface

In this work, ANFIS model was used to predict bubble point pressure of crude oils. Data needed to design and train the presented model were extracted and collected from articles which investigated the bubble point pressure of crude oils by literature Bandyopadhyay and Sharma, 2011 [13]. Based on obtained results, designed ANFIS model has good accurate and able to predict bubble point pressure of crude oils, because of the integration of fuzzy logic systems with the capability of learning in artificial neural networks which leads to the adaptability of the model with this issue.

4. CONCLUSIONS

A new model has been developed for prediction of Bubble point Pressure of crude oil samples. The model used temperature–concentration interaction terms to portray the fluid behavior. The following conclusions summaries the results of this study:

1- The comparison among experimental results and neural-fuzzy shows that prediction of designed model is well matched with experimental data with absolute relative and average absolute deviation errors which are 0.035033 and 0.088093respectively.

2- Comparing obtained results determines showed that ANFIS model is more accurate than other models to predict Bubble point Pressure of crude oil.

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