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Development of PVT Correlation for Iraqi Crude Oils Using Artificial Neural Network

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Abstract
Several correlations have been proposed for bubble point pressure, however, the correlations could not predict bubble point pressure accurately over the wide range of operating conditions. This study presents Artificial Neural Network (ANN) model for predicting the bubble point pressure especially for oil fields in Iraq. The most affecting parameters were used as the input layer to the network. Those were reservoir temperature, oil gravity, solution gas-oil ratio and gas relative density. The model was developed using 104 real data points collected from Iraqi reservoirs. The data was divided into two groups: the first was used to train the ANN model, and the second was used to test the model to evaluate their accuracy and trend stability. Trend test was performed to ensure that the developed model would follow the physical laws. Results show that the developed model outperforms the published correlations in term of absolute average percent relative error of 6.5%, and correlation coefficient of 96%.

Introduction
Reservoir fluid properties are very important in reservoir engineering computations such as material balance calculations, well test analysis, reserve estimates, and numerical reservoir simulations. Ideally, these properties should be obtained from actual measurements. Quite often, however, these measurements are either not available, because of one or more of these reasons:

a) Samples collected are not reliable.
b) Samples have not been taken because of cost saving.
c) PVT analyses are not available when needed.

This situation often occurs in production test interpretation [1].

In such cases, empirically derived correlations are used to predict the needed properties. All computations, therefore, will depend on the accuracy of the correlations used for predicting the fluid properties [2].

Bubble point pressure is defined as the pressure at which the first gas bubble evolves from liquid phase, thus differentiating between single and multi-phase state of reservoir fluids [3].

There are many empirical correlations for predicting PVT properties, most of them were developed using linear or non-linear multiple regression or graphical techniques. Each correlation was developed for a certain range of reservoir fluid characteristics and geographical area with similar fluid compositions and API gravity. Thus, the accuracy of such correlations is critical and it is not often known in advance [2].

Precise prediction of bubble point pressure (Pb) is very important in reservoir and production computation.

ANNs are biologically inspired non-algorithmic, non-digital, massively parallel distributive and adaptive information processing systems. They resemble the brain in acquiring knowledge through learning process, and storing knowledge in inter-neuron connection strengths [3].

The objective of this study is to develop new predictive models for Pb based on artificial Neural Networks (ANN) using field data collected from oil fields in Iraq.

PVT Empirical correlations

For the last 60 years, engineers realized the importance of developing and using empirical correlations for PVT properties. Studies carried out in this field resulted in the development of new correlations. Standing [4,5] in 1947 and 1977 presented correlations for bubble point pressure and for oil formation volume factor. Standing's correlations were based on laboratory experiments carried out on 105 samples from 22 different crude oils in California. Glaso[6] (1980) developed correlation for Pb using 45 oil samples from North Sea hydrocarbon mixtures. Al-Marhoun[7] (1988) published correlations for estimating bubble point pressure and oil formation volume factor for the Middle East oils. He used 160 data sets from 69 Middle Eastern reservoirs to develop the correlation. Dokla and Osman[8] (1992) published set of correlations for estimating bubble point pressure and oil formation volume factor for UAE crudes. They used 51 data sets to calculate new coefficients for Al Marhoun[7] Middle East models. Al-Yousef and Al-Marhoun[9] (1993) pointed out that the Dokla and Osman [8,10] in 1992 and 1993 bubble point pressure correlation was found to contradict the physical laws. Macary and El-Batanoney [11] (1992) presented correlations for bubble point pressure and oil formation volume factor. They used 90 data sets from 30 independent reservoirs in the Gulf of Suez to develop the correlations. The new correlations were tested against other Egyptian data of Saleh et al.[12](1987) and showed improvement over published correlations. In 1993, Petrosky and Farshad [13] developed new correlations for Gulf of Mexico crude oils. Standing [4] (1947) correlations for bubble point pressure, solution gas oil ratio, and oil formation volume factor were taken as a basis for developing their new correlation coefficients. Ninety data sets from the Gulf of Mexico were used in developing these correlations. Al-Mehaideb [14] (1997) published a new set of correlations for UAE crudes using 62 data sets from UAE reservoirs. These correlations were developed for bubble point pressure and oil formation volume factor. The bubble point pressure correlation like that of Omar and Todd [15](1993) uses the oil formation volume factor as input in addition to oil gravity, gas gravity, solution gas oil ratio, and reservoir temperature. Elsharkawy et al.[16] (1994) evaluated PVT correlations for Kuwaiti crude oils using 44 samples. Standing[4] (1947) correlation gave the best results for bubble point pressure while Al-Marhoun[7] (1988) oil formation volume factor correlation performed satisfactory. Finally, Al-Shammasi[17] (1997) evaluated the published correlations for bubble point pressure and oil formation volume factor for accuracy and flexibility to represent hydrocarbon mixtures from different geographical locations worldwide. He presented a new correlation for bubble point pressure based on global data of 1661 published and 48 unpublished data sets. He concluded that statistical and trend performance analysis showed that some of the correlations violate the physical behavior of hydrocarbon fluid properties.

A list of some correlations found in literature is summarized in Table (1).

Table 1, Summary of the previous correlations

Researchers	Correlations
Standing (1947)	$Pb=18.2[(Rs/\gamma g)^{0.83}\ (10)^{a}\ -1.4]$ $a=0.00091(T-460)-0.0125(API)$
Glaso (1980)	$Log(Pb)=1.7669+1.7447\log(p_b^*)-0.30218[\log(p_b^*)]^2$ $P_b^*=(Rs/\gamma g)^{0.816}(T)^{0.172}(API)^{-0.989}$
Al-Marhoun (1988)	$Pb=5.338088*10^{-3}\ Rs^{0.715082}\ \gamma g^{-1.87784}\ \gamma o^{3.1437}\ T^{1.32657}$
Dokla and Osman (1992)	$Pb=0.836386*10^{4}\ \gamma g^{-1.01049}\ \gamma o^{0.107991}\ T^{-0.952584}\ Rs^{0.724047}$
Petrosky and Farshad (1993)	$Pb=[112.727Rs^{0.577421}/\gamma g^{0.8439}\ (10)^{x}] - 1391.051$ $X=7.916(10^{-4})(API)^{1.5410} - 4.561\ (10^{-5})(T-460)^{1.3911}$

PVT Neural Network Models

Artificial neural networks are parallel-distributed information processing models that can recognize highly complex patterns within available data. In recent years, neural network have gained popularity in petroleum applications. Many authors discussed the applications of neural network in petroleum engineering. Few studies were carried out to model PVT properties using neural networks [2]. In 1996, Gharbi and Elsharkawy[18] published neural network models for estimating bubble point pressure and oil formation volume factor for Middle East crude oils. They used two hidden layers neural networks to model each property separately. The bubble point pressure model had eight neurons in the first layer and four neurons in the second. The formation volume factor model had six neurons in both layers. Both models were trained using 498 data sets collected from the literature and unpublished sources. The models were tested by other 22 data points from the Middle East. The results showed improvement over the conventional correlation methods with reduction in the average error for the bubble point pressure oil formation volume factor. Gharbi and Elsharkawy[19] (1997) presented another neural network model for estimating bubble point pressure and oil formation volume factor for universal use. They used three-layer neural network model to predict the two properties. They developed the model using 5200 data sets collected from all over the world representing 350 different crude oils. Another set of data consisting of 234 data sets was used for verifying the results of the model. The reported results for the universal model showed less improvement than the Middle East neural model over the conventional correlations. The bubble point pressure average error was lower than that of the conventional correlations for both training and test data. Finally, Varotsis et al.[20] (1999) presented a novel approach for predicting the complete PVT behavior of reservoir oils and gas condensates using Artificial Neural Network (ANN). The method uses key measurements that can be performed rapidly either in the lab or at the well site as input to an ANN. The ANN was trained by a PVT studies database of over 650 reservoir fluids originating from all parts of the world. Tests of the trained ANN architecture utilizing a validation set of PVT studies indicate that, for all fluid types, most PVT property estimates can be obtained with a very low error which is considered better than that provided by tuned Equation of State (EOS) models, which are currently in common use for the estimation of reservoir fluid properties. In addition to improved accuracy, the proposed ANN architecture avoids the ambiguity and numerical difficulties inherent to EOS models and provides for continuous improvements by the enrichment of the ANN training database with additional data.

Data Acquisition

Data set used to implement the ANN model was obtained from experimental work and fields testing, this data set consists of 104 observations collected from Iraqi oil fields.

Each data set contains the following data observations: (1) reservoir temperature (T), (2) oil gravity (γ_o), (3) solution gas-oil ratio (Rs), (4) gas relative density (γ_g), (5) bubble point pressure (Pb).

Development of ANN Based Correlation

Database Generation

Collecting data is the preliminary step for building ANN. Bubble point pressure values were collected from many Iraqi crude oils as aforementioned. Selected parameters affecting the bubble point pressure, which is the target of this simulation, were investigated via literature survey. These parameters were organized into four inputs to be fed to the ANN. The range of the input parameters as well as the desired parameter is given in Table (2). By examining this table, one can see the wide range and the complex relationship of the input and the output parameters, studied in the present study. Building ANN with the optimal structure depends mainly on careful planning for the necessary information fed to the network as the input layer.

Table 2, The range of input and output parameters

	Parameter	Range
Input	Solution gas-oil ratio	183.049 – 1799.9 scf/STB
	Stock tank oil relative density (water=1)	0.815 – 0.9575
	Gas relative density (air=1)	0.723 – 1.7577
	Reservoir temperature	510 – 805.5 (R°)
Output	Bubble point pressure	550.03 – 4409.369 psia

Training of Artificial Neural Network

Training was accomplished using Neuro Solutions by Excel version 5, supplied by Neuro Dimension, Inc. copyright 1997-2005.(MLPs) type was used which is multilayered feed forward network, trained with static backpropagation of error. 67% of the collected data was set as training, 33% as testing. It computes the error in a test set at the same time that the network is being trained with the training set. It is known that the error will keep decreasing in the training set, but may start to increase in the test set. This happens when the network starts "memorizing" the network pattern [21].

The use of ANN to predict the bubble point pressure was implemented using two kinds of networks. The first ANN consists of an input layer with four input PEs, corresponding to the four input parameters (stated before); one hidden layer, and output layer of one PEs representing the bubble point pressure. The second had the same structure except having two hidden layers. Many trials were made to find the best topology of the (MLPs).

The training process starts with randomly chosen initial weight values. Then a back-propagation algorithm is applied after each iteration, the weights are modified so that the cumulative error decreases. In back-propagation, the weight changes are proportional to the negative gradient of error. Back-propagation may have an excellent performance; this algorithm is used to calculate the values of the weights and the following procedure is then used (called "supervised learning") to determine the values of weights of the network:-

1. For a given ANN architecture, the value of the weights in the network is initialized as small random numbers.
2. The input of the training set is sent to the network and the resulting outputs are calculated.
3. The measurement of the error between the outputs of the network and the known correct (target) values is calculated.
4. The gradients of the objective function with respect to each of the individual weights are calculated.
5. The weights are changed according to the optimization search direction.
6. The procedure returns to step 2.
7. The iteration terminates when the value of the objective function calculated using the data in the test approaches experimental value.

The learning process includes the procedure when the data from the input neurons is propagated through the network via the interconnections. Each neuron in a layer is connected to every neuron in adjacent layers. A scalar weight is associated with each interconnection. Neurons in the hidden layers receive weighted inputs from each of the neurons in the previous layer and they sum the weighted inputs to the neuron and then pass the resulting summation through a non-linear activation function (hyperbolic tan function) [21, 23].

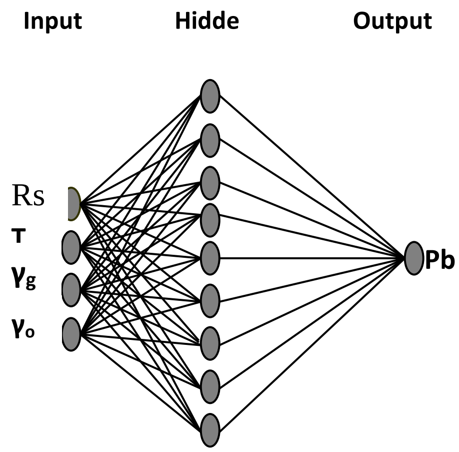

Fig.1, ANN structure of present study

Results and Discussions

The selection of number of hidden layer neurons (perceptrons or PEs) is very important and troublesome. After training the neural network, with 67% of the randomized data sets (70 data points), the models become ready for testing and evaluation. To perform this, the last data group (34 data points) which was not seen by the neural network during training was used. For the purpose of finding the best architecture of the network, the testing % AARE and the correlation coefficient (% R) which should be around unity, are calculated and compared for each topology and for each correlations. Therefore, after careful training of the network, testing showed that ANN structure of [4-9-1] as shown in Fig.(1), using the activation function of (tanh), momentum rate of 0.7 and after 5000 iteration, had correlated the bubble point pressure with reservoir temperature, oil gravity, solution gas-oil ratio, and gas relative density, successfully. The result of prediction is plotted with experimental values as shown in Figs (2) and (3).

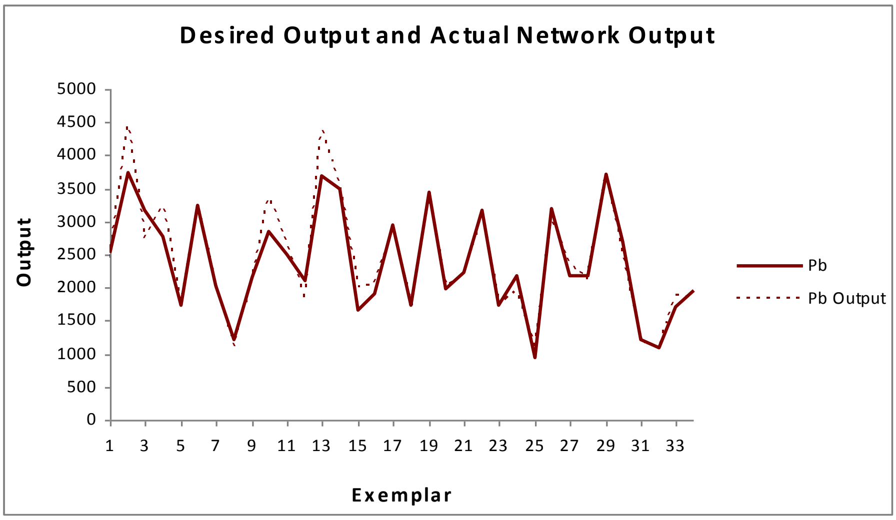

Fig.2, Desired (measured) and actual (predicted) values vs. testing exemplars

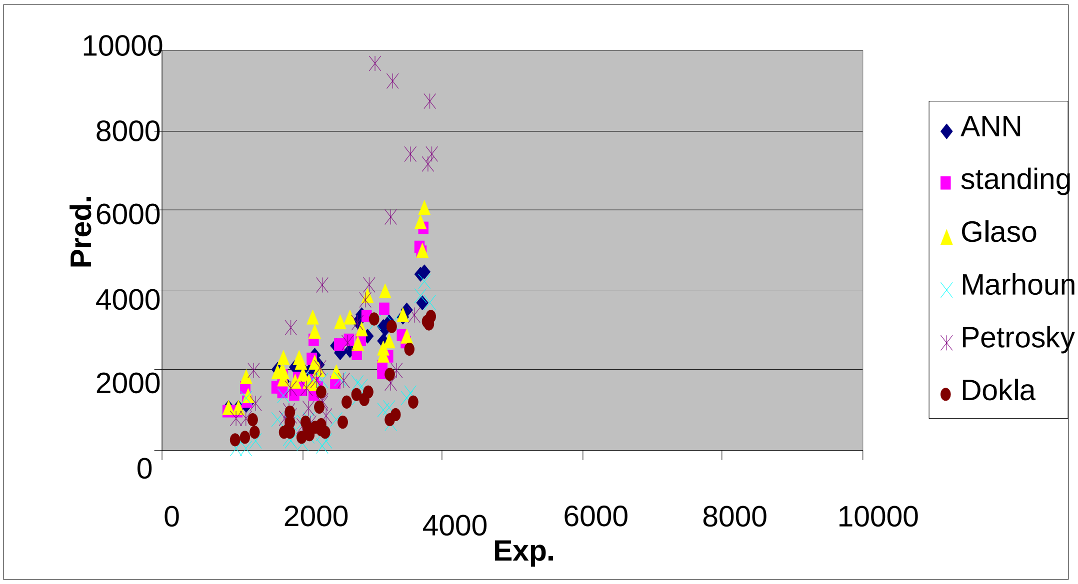

Fig.3, Predicted values vs. observed values to ANN and previous works

Table 3, Comparison of the present results with previous work

Correlations	AARE%	R%	Sx%
Standing (1947)	22.6	80.8	30.7
Glaso (1980)	17.8	81.4	22.5
Al-marhoun (1988)	103.7	68	139.2
Dokla and Osman (1992)	69	77.6	91.7
Petrosky and Farshad (1993)	36.8	74.3	45.9
ANN (present study)	6.5	96	9.3

Conclusions

1. A model was developed to predict the bubble point pressure for Iraqi crude oils. The model was based on artificial neural network, and developed using 104 data points collected from different Iraqi fields.
2. It was concluded that the structure of [4-9-1] was chosen as the best to implement the target of the present study. MLP architecture of four neurons in the first layer which are the four inputs to the network; solution gas –oil ratio, tank oil relative density, gas relative density and reservoir temperature. Nine neurons were in the second layer(i.e. hidden layer), and one neuron in the third layer which accounts for the bubble point pressure in the output layer.
3. In addition, the developed Pb model outperforms the previous published empirical correlations. Also the present study supports the idea of developing local / regional models rather than universal ones. The results show that the developed model provides better prediction and higher accuracy than published empirical correlations, with an average absolute Percent Relative Error of 6.5% and Correlation coefficient of 96%.

Nomenclature

Pb = bubble point pressure Psia
Rs = Solution gas-oil ratio (scf/STB)
T = Temperature (R°)
γo = Stock tank oil relative density (water=1)
γg = Gas relative density (air=1)
Sx = Standard Deviation
R = Correlation coefficient

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