PREDICTION OF RESERVOIR PERMEABILITY FROM WIRE LOGS DATA USING ARTIFICIAL NEURAL NETWORKS

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Abstract

This paper presents a methodology to predict reservoir permeability from well logs data by using an artificial intelligence technique namely artificial neural network. A multilayered perceptron trained by backpropagation algorithm was used to build the predictive model. The performance of the net results was measured by correlation coefficient. The implemented artificial neural network model is demonstrated by applying it to Mishrif limestone reservoir at Nasyria oil field, south of Iraq. The results show that artificial neural network was capable of reproducing permeability (horizontal and vertical) with very high accuracy, so that the calculated correlation coefficients for horizontal and vertical permeability were 0.85 and 0.90, respectively. The results could be generalized to other field after examining new data, and a regional study might be possible to study reservoir properties in south of Iraq with cheap and very fast constructed models.

Key Words: Artificial neural network, Mishrif Formation, Permeability, Artificial intelligence

تخمين نفاذية صخور المكمن النفطي من قراءات المجسات البئرية باستخدام تقنية الشبكات العصبية الصناعية

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الخلاصة

يتطرق البحث الحالي الى امكانية استخدام احدى تقنيات الذكاء الصناعي المعروفة باسم الشبكات العصبية الصناعية للتنبؤ بقيم نفاذية الصخور المكمنية باستخدام المجسات البئرية المختلفة. بني نموذج الشبكة العصبية الصناعية اعتماداً على معمارية النوع الشائع منها وهي الشبكة العصبية المتعددة الطبقات واستخدمت طريقة الانسياب للخلف لغرض تدريبها (معايرتها). تم تقييم ادائية الشبكة العصبية باستخدام معامل الارتباط التربيعي. طبق نموذج الشبكة العصبية المعاير للتنبؤ بقيم النفاذيات (الافقية والعمودية) على تكوين المشرف في حقل الناصرية ، جنوب العراق. بينت النتائج الامكانية العالية جداً لنموذج الشبكة العصبية للتنبؤ بقيم النفاذيات فقط باستخدام قراءات المجسات البئرية لخمس مجسات شائعة هي مجس النيوترون والمجس الصوتي ومجس الكثافة ومجس الحث العميق ومجس اشعة كاما. خرجت الدراسة بنتيجة مفادها امكانية استخدام مثل هذه التقنيات الحديثة وغير المكلفة في حقل جيولوجيا النفط في العراق.

Introduction

Permeability is one of the most important characteristic of hydrocarbon bearing formation which reflects the ability of rocks to transmit fluids in the presence of a potential energy gradient. Understanding the spatial distribution of this property is fundamental to the successful exploitation and reservoir management. Determination of permeability of rocks is a major problem in petroleum industry because of its inherent non-linear dependency on rocks and fluid contained within them such as porosity, irreduciable water saturation, shale volume, tortusity, pore connectivity and other factors associated with well conditions or formation damage. To date, there are three generally reliable ways of acquiring knowledge on rock permeability. These are: (1) direct measurement of rock sample (cores). (2) empirical models that relate permeability to parameters calculated from well logs such as porosity and water saturation, and (3) by using artificial intelligence (AI) techniques such as artificial neural network, fuzzy inference system, and genetic algorithm.

During the last few decades, AI techniques have become increasingly popular in the petroleum industry. Resent examples include permeability prediction with artificial neural networks (ANNs) from well logs data [1] [2], generation of synthetic wireline logs from other logs [3] [4], identification of lithological and depositional facies via competitive neural network and fuzzy logic [5] [6], and estimation of reservoir permeability using integration of genetic algorithm and a coactive neuro-fuzzy inference system [7]. These computational techniques offer real advantage over conventional modeling, including the ability to handle large amounts of noisy data from dynamic and non-linear systems without a prior assumption of the process involved, and give a good solution even when input data are incomplete or ambiguous.

The aim of this article is to use artificial neural networks to estimate horizontal and vertical permeability of Mishrif Formation at Nasyria oil field, south of Iraq, from well logs data, and to use acquired knowledge in a predictive sense. The objective also involves trying to introduce these efficient techniques to oil industry of Iraq as alternative approaches to highly expensive traditional physically based models.

Artificial Neural Network

An artificial neural network (ANN) model is a flexible mathematical structure capable of describing complex non-linear relation between input and output data sets. The architecture of ANN models is loosely based on biological nervous system [8]. A neural network is composed of many processing elements, called neurons, operating in parallel. Each neuron is connected to other neurons via links of variable weights. The weights represent information being used by the network to solve a specific problem [9]. Basically, there are different types of ANN according to their architecture: recurrent and feed-forward. Beside the architecture, three different learning paradigms are developed, each corresponding to a particular abstract learning task. These are unsupervised, supervised, and reinforcement. In unsupervised learning the ANN is presented to some data without getting any teacher information. This type of learning is often used for data clustering and data analysis. In supervised learning, data is presented together with the teacher information in order to associate the data with the teacher signal. This type of learning is often used for classification and function approximation. In reinforcement learning, data is usually not given, but generated by an agent's interactions with the environment.

The most popular ANN architecture is the multilayered perceptron (MLP) trained with Backpropagation (BP) algorithm. A MLP network consists of an input layer, one or more hidden layer of computation neurons, and an output layer. The number of input and output neurons is determined by the actual number of input and output variables. The number of hidden layers and neurons are determined by trial and error procedure, and depend on the complexity of the problem under consideration. The schematic diagram of a three-layer MLP is shown in Figure 1. Each neuron in a layer receives weighted inputs from a previous layer and transmits its output to the neuron in the next layer. The summation of weighted input signal is calculated by using the following equation: (Figure 2)

$$y_{net} = \sum_{i=1}^{n} x_i w_i + w_b \qquad (1)$$

where y_{net} is the summation of weighted input, x_i is the neuron input, w_i is weight associated with each neuron input, w_b is bias, and n is number of examples (instants). The results from equation 1 is transformed by a non-linear activation function given by

$$y_{out} = f_{(net)} = \left(1 + e^{-y_{net}}\right)^{-1} \qquad (2)$$

where y_{out} is the response of neural network system, $f_{(net)}$ is the non-linear activation function.

The responses of neural network system are compared with the target values through an error statistic namely mean square error given by:

$$MSE = \frac{1}{2}\sum_{i=1}^{n}\left(y_i^{obs} - y_i^{out}\right) \qquad (3)$$

where y_i^{obs} and y_i^{out} are the observed and predicted values, respectively.

Training in ANNs (sometimes called learning) involves feeding samples as input vectors through designed network, calculating the error of the output layer, and then adjusting the weight of the network to minimize error. Training can stop when the network error drops below a specified threshold. In this study, BP learning algorithm, a supervised learning is used. Standard BP is a gradient descent algorithm in which the network weights are moved along the negative of the gradient of the performance function. The term BP refers to the manner in which gradient is computed for non-linear multilayer network.

BP algorithm consists of two passes through the different layers of the network: a forward pass and backward pass [8]. In the forward pass the input signal propagate through the network in forward direction, layer by layer. Finally, a set of outputs is produced. In the backward pass, the weights are all adjusted according to a correction rule. The output of the network is subtracted from the target values to produce an error term. This error is then propagated backward through the network. The weights can be updated one by one or by a batch mode. In a batch mode, the descent is based on the gradient ∇E for the total training set according to the following equation: [9]

$$\Delta w_{ij}(n) = -\eta^{*}\frac{\partial E}{\partial w_{ij}} + \alpha^{*}\Delta w_{ij}(n-1) \qquad (4)$$

where η and α are the learning and momentum parameters, respectively. The momentum term determines the effect of past weight changes on the current direction of movement in the weight space. A good choice of these parameters is required for the training success and the speed of the neural network learning.

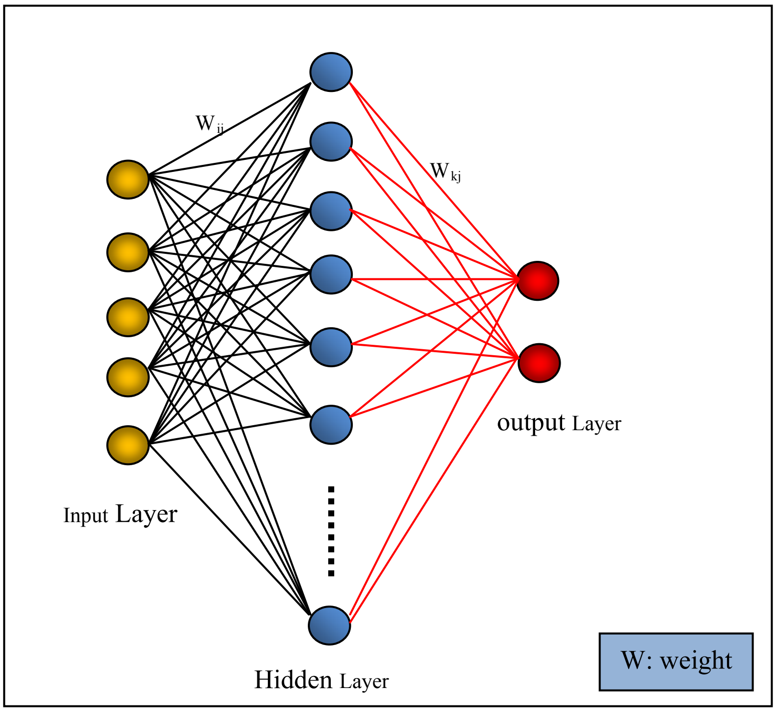

Figure 1: A simple multilayered perceptron with one hidden layer.

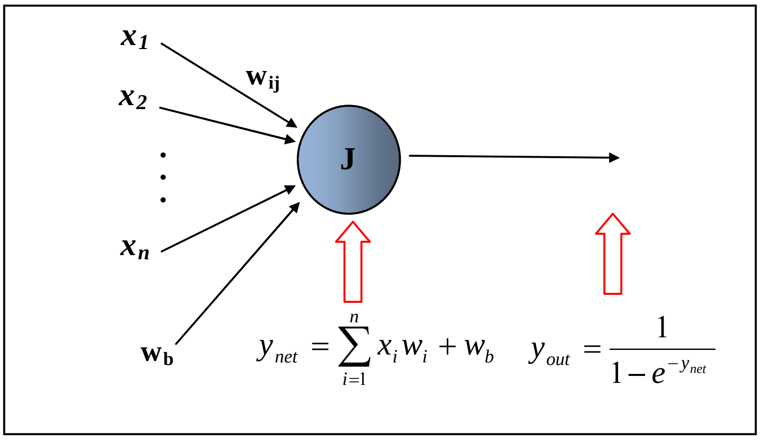

Figure 2: The schematic representation of a neuron

Description of the Reservoir

The field under study is located in south of Iraq between latitudes (34°80′- 34°60′ N) and longitudes (57°50′ -60°10′ E), Figure 3. It is anticline structure with northwest- southeast general trend. Three reservoir units contain most of the oil within the reservoir; the Yamam, Nahr Umr, and Mishrif Formations. This study is focused on Mishrif Formation which is the most promising productive unit in the study area.

The Mishrif Formation represents a heterogeneous formation originally described as organic detrital limestones with beds of algal, rudist, and coral-reef limestones, capped by limonitic fresh water limestones [10]. The abundant fauna listed by Bellen et al. [10] indicates that the formation is of Cenomanian-Early Turonian age. The formation was deposited as rudist shoals and patch reefs over growing subtle structural highs developing in an otherwise relatively deeper shelf on which marine sediments of the Rumaila Formation were deposited [11]. The lower boundary of the formation is conformable. The underlying unit is usually the Rumaila Formation. The upper contact is unconformable and this unit overlay the Muddud Formation. Porosity of the formation is up to 22%, and permeability ranges from 23 to 775 md, which reflects the high degree of heterogeneity. The API gravity of oil is typically 23- 36.6°, averaging around 25° [12].

Methodology

A total of 103 core permeability (horizontal and vertical) measurements and their corresponding well logs data from two exploration wells (Ns-5 and Ns-3) were attained from archive of South Oil Company (SOC), and were used to build the network model. The used well logs data include gamma ray (GR), bulk density log (MFDL), compressional sonic log (DT), neutron log (DT), and induction log (ILD). Because of the vast distribution of the permeability data, logarithmic scale was used. The basic statistics of input and output variables (well logs data and permeability data, respectively) are summarized in Tables 1 and 2 for training and testing data sets.

Selection of input variables for AI model is a very important and critical step. The gamma ray log responses provide evidence of clay that has an impact on permeability. The bulk density, sonic, and neutron are inverse functions of porosity and shale content; therefore they contribute to the permeability of the formation [1]. Deep induction log usually used to calculate water saturation in rocks since water saturation may or may not be an indication of water movement in the rock through the geological time it may have some contribution to rock permeability [2].

The neural network toolbox in MATLAB 2007b was used in this study. The ANN model was based on a MLP with one hidden layer. The original data (input and output) were processed through two steps: data normalization and data set partition. Generally, the original data consists of different parameters with different physical meaning and units, and thus their degrees are highly variable. To ensure that each variable is treated equally in a model, data are usually rescaled to a certain interval such as [-1, 1] [0, 1] or other scaling criterion. The mapminmax scaling function was used to normalize data set in the range [-1, 1]. After normalization, data set was divided into three parts: 60% for training, 20% for validation, and 20% for testing.

The optimal number of hidden nodes is 20 as determined by trial and error method. In training, BP is applied using the Levernberg-Marqurdrat implementation. The logistic sigmoid and linear activation functions are used in the hidden and output layer, respectively. The learning and momentum parameters that give best results are 0.06 and 0.8, respectively. Early stopping technique is used to ensure that the network would not overfit the training data, but rather has a good generalization as the key goal [8]. The performance of the implemented network was evaluated by using squared correlation coefficient (R2). The R2 measures the linear correlation between the observed and predicted values; the optimal value is one. It is calculated using the following equation:

$$R = \frac{\sum_{i=1}^{n}\left(y_i^{obs} - \bar{y}\right)\left(y_i^{out} - \hat{y}\right)}{\sqrt{\sum_{i=1}^{n}\left(y_i^{obs} - \bar{y}\right)^2\left(y_i^{out} - \hat{y}\right)^2}} \quad (5)$$

where $\bar{y}$ and $\hat{y}$ are averages of observed and predicted permeability, respectively.

Results and Discussion

The cross plots of measured permeabilties (horizontal and vertical) against network prediction results are shown in Figure 4 and Figure 5 for testing data set (Ns-1 well). The high correlation coefficients, 0.86 and 0.90 for horizontal and vertical permeabilities indicate that ANN model implemented here is capable of producing results with high accuracy, despite the high degree of heterogeneity of interested reservoir. The developed ANN in this study could be used to predict permeability from wire logs data for new wells in the same field without the need for very expensive coring process.

Conclusion

1. The developed ANN model for Mishrif reservoir in Nasyria oil field is capable of estimating formation permeabilites with a high accuracy by using only well log data for five conventional logs.
2. By adding additional parameters such as depth to ANN model input could increase the capability of the model but it may constrain the extrapolation capability of it.

Determination of permeability from other artificial intelligence and machine learning techniques such as neuro-fuzzy inference system and model trees by applying a single technique or a hybrid from one or more techniques is recommended for future work.

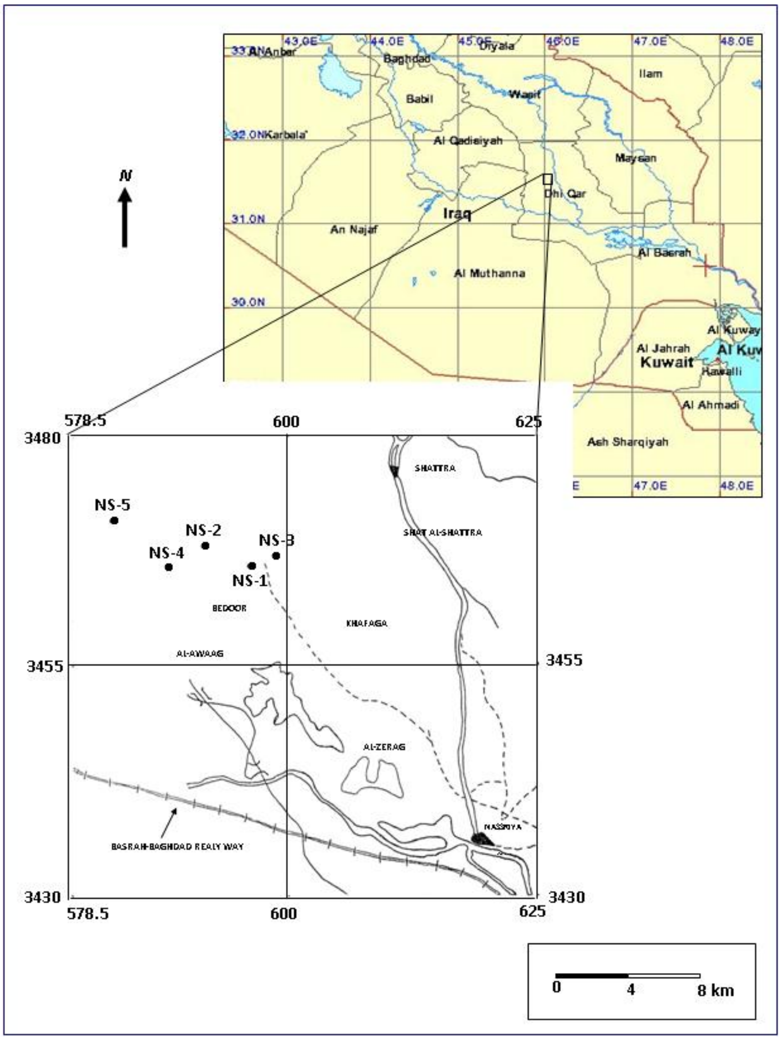

Figure 3 : Location map of the study area

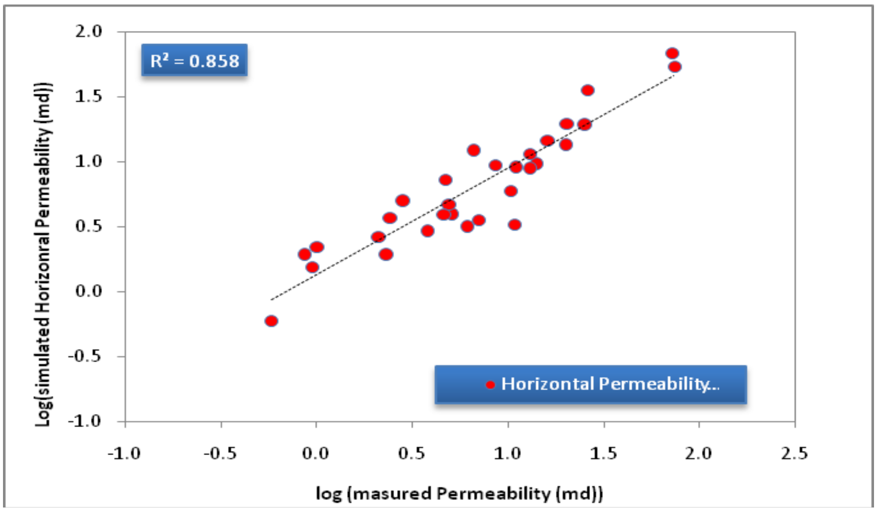

Figure 4: The comparison between measured and predicted horizontal permeability for (Ns-3 well)

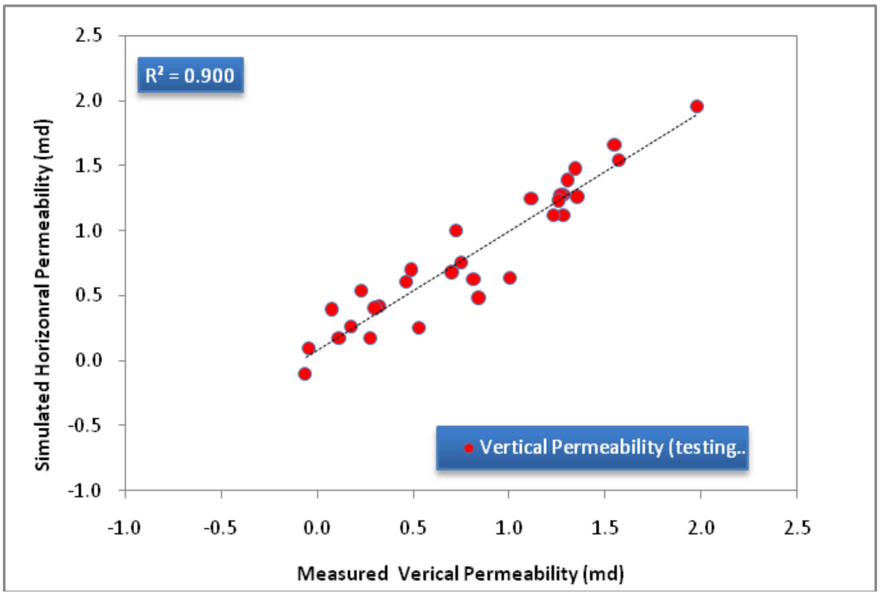

Figure 5: The comparison between measured and predicted vertical permeability for (Ns-3 well)

Table 1: Basic statistics of the input and output data for training data set (Ns-5)

Variable	Min.	Max.	Mean	St.Dev
Gamma Ray log (API)	14.500	47.000	20.548	6.735
Bulk Density log (gm/cm^3)	2.050	2.650	2.384	0.127
Sonic log (µs/ft)	58.300	114.000	27.350	9.960
Neutron log (%)	11.000	45.000	21.267	7.213
Deep Induction log (Ω.m)	0.858	20.000	5.945	5.051
Log horizontal permeability (K_h) (md)	-2.377	1.724	-0.122	0.954
Log vertical permeability (K_v) (md)	-2.201	1.919	-0.084	0.977

Table 2: Basic statistics of the input and output data for testing data set (Ns-3)

Variable	Min.	Max.	Mean	St.Dev
Gamma Ray log (API)	13.850	30.000	18.870	4.022
Bulk Density log (gm/cm^3)	2.240	2.362	2.312	0.0336
Sonic log (µs/ft)	86.300	73.080	79.560	3.910
Neutron log (%)	21.000	29.3000	24.810	2.369
Deep Induction log (Ω.m)	0.450	25.000	3.780	6.120
Log horizontal permeability (K_h) (md)	-0.2366	1.869	0.823	0.528
Log vertical permeability (K_v) (md)	-0.060	1.973	0.807	0.550

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