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Review Article

Sandstone Reservoirs Porosity and Water Saturation Estimation Using Functional Network Techniques

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ABSTRACT

An accurate determination of porosity and water saturation is vital for evaluating an oil reserve and proposing a development plan for developed sandstone reservoir. The objective of this study is to provide an improved intelligent approach the use of functional networks to estimate porosity and water saturation from well log using real field data in sandstone reservoir where it becomes difficult to acquire reliable well logging data. The proposed methodology makes use of appropriate well logs and core measurements. A portion of the data available was retained for verification of the prediction of water saturation and porosity. This paper presents a novel method for estimating these two important parameters directly from conventional well measurements. The recently proposed Functional Networks technique is applied for rapid and accurate prediction of these parameters, using six and five basic well log measurements as data for estimating porosity and water saturation respectively. Functional network is a generalization of the conventional Feed Forward Neural Networks, which overcome many of the drawbacks of the conventional neural network techniques. The proposed functional network was trained using data gathered from two wells in the Middle East region. Results obtained from this case study of sandstone reservoir using the proposed intelligent technique have shown to be fast and accurate referring to core samples porosity and water saturation values.

Keywords: Functional networks; Neural networks; Porosity; Water saturation; Well logs

INTRODUCTION

The major objective of the petroleum industry is to obtain an accurate estimate of the hydrocarbon in place; this is required either at early stage of the well for exploitation or for developed reservoir management. An accurate determination of porosity and water saturation parameters is a must for evaluating any reservoir and drafting any development plan for developed reservoir. Porosity is described as the ratio of the aggregate volume of interstices in a rock to its total volume whereas water saturation is defined as the fraction of pore volume of formation rock which is filled with water only. The rest of the pore space is assumed to be filled with either oil or gas. Therefore, inaccurate determination of water saturation leads to either underestimation or overestimation of reserves.

The most accurate method for determination of these important properties is mostly done by core analysis at expensive laboratory tests. However, the core data are not always available for most wells in a given field or at every depth levels either due to the borehole condition or the high cost of obtaining cores [1]. Hence, log measurements, which are usually available, are utilized by correlating well logs with core data of the cored wells and subsequently using the correlation model to predict these properties at the uncared intervals and wells. Well logs approach can provide a continuous record over the entire well, and it is economical and quick to obtain.

Many empirical equations are available to transform well log data to porosity and water saturation. For example, porosity has been related to sonic transit time and density logs. On the other hand, water saturation can also be determined from empirical formulas using resistivity, gamma ray logs and porosity estimates. Besides the fact that these empirical models are not sufficiently accurate, they are not universally applicable as they should be tuned to the area of work which requires the estimation of

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parameters in the laboratory, and some of these model parameters are not easily obtainable (Helle et al. [2] and Yan [3].

Parametric methods like statistical regression is another versatile approach used in estimation of these properties, where a functional relationship is developed between the core data and well log data [3]. This however requires the assumption and satisfaction of multi-normal behaviors and linearity [4]. Therefore, neural networks, or more specifically, multilayer perceptrons (MLP), have been increasingly applied to predict reservoir properties using well log data [4-6].

Neural networks are characterized as computational models with abilities to adapt, learn, generalize, recognize, and organize data. The advantages of neural networks include its high computational efficiency, adaptability, non-linear characteristics, generation properties, fault tolerance, freedom from a priori selection of mathematical models, and ease of working with high-dimensional data [7]. Neural networks have been demonstrated in several practical applications for estimation of porosity and water saturation from well logs for example, see [8-14]. Despite its wide applications, the MLP has some draw- back including; slow convergence on learning; complexity of design space; random initialization of weight and local minimal problem. Therefore, MLP are useful when the network architecture and parameters, which are often done by trial and error approach are chosen correctly. A common approach is to train as many networks as possible and select the one that yields the best generalization performance. Hence the solution may not be a unique solution.

Recently, Castillo et al. [15-18], introduced functional network as a powerful extension and network- based alternative to the neural networks paradigm. In functional networks, neural functions are to be learned instead of weights. In addition, outputs coming from different neurons can be connected, that is, forced to output the same values. The topology and neuron functions of functional networks can be selected based on data, domain knowledge, or a combination of the two. This kind of networks exhibits more versatility than neural networks so they can be successfully applied to several problems.

The objective of this study is to provide an improved intelligent approach via the use of functional networks to estimate porosity and water saturation from well log using real field data. The proposed methodology makes use of appropriate well logs and core measurements. A portion of the data available was retained for verification of the prediction results.

FUNCTIONAL NETWORKS

Functional networks (FN) consist of the following elements:

- A layer of nodes for receiving the input data (xi; i=1, 2, 3, 4), another layer for the output data (x7) and none, one or more layers for intermediate information (x5 and x6);
- Processing units, (fi) that evaluate a set of input values and delivers a set of output values,
- A set of directed links.

Functional networks extend the standard neural networks by allowing neuron functions fi to be not only true multi-argument and multivariate functions, but to be different and learnable, instead of fixed functions. In addition, the neuron functions in functional networks are unknown functions from a given family, such as, polynomial, exponential, Fourier, wavelet …etc., to be estimated during the learning process.

Functional networks model

The first step in functional networks is the specification of the initial topology which is problem driven. However, if there is no idea of the problem domain (like in our case), a generalized.

Simplification of the model

For the problem concerned in this study, the model represented by (3) was simplified further to reduce complexity of terms to be estimated by assuming that all the coefficients of the cross multiplication terms between functions of different variables is zero.

Data acquisition and processing

In this study, we used data set from the Middle Eastern region containing well logs, core porosity and water saturation from two wells labeled, A and B of 206 and 211 observations respectively. The two wells were combined together and divided randomly into two sets, training and testing sets of 70% and 30% of data respectively. In order to make sure the predictors variables are independent from measurement units (since they are of different units), the predictor variables (inputs) were normalize between 0 and 1. The training set is then used to learn the coefficients in (11) for estimation of porosity and water saturation. Several basis functions basis such as polynomial, Fourier, exponential, and logarithms were tried in order to select the one that will give best approximation for each function (h1(x1), h2(x2),…). The coefficients of the network is optimized by backward-forward search method using Minimum description length (MDL) criteria to determine the best contributing coefficients to the network as well as best functional basis to use by choosing the one with lowest value of MDL as used in [18,19]. All experiments were performance on a fedora 9 Linux machine.

Estimation of porosity with FN

This section discusses estimation of formation porosity with functional networks using the model (6) discussed above. Six well log measurements namely; Sonic log (DT), Neutron log (NPHI), Density log (RHOB), Gamma Ray (GR), Laterlog (Rt), and Photoelectric Factor log (PEF) were used as inputs to the networks. The functional network model is able to predict formation porosity with Fourier basis function as the best basis, achieving a root mean square error (RMSE) of 0.0293 and correlation coefficient (CC) of 0.9158 for the training set, RMSE of 0.0245 and CC of 0.9343 for the testing set. The result for the estimation the scatter plot for the best selected model from the basisfunctions. The plot shows that there is a good matching between the core porosity and estimated porosity. Equation (12) shows the relationship between the predictor variable and the core porosity for the best model.

Estimation of water saturation with FN

Similarly, water saturation was determined with the same model and procedure above using five well log measurements inputs; NPHI, RHOB, GR, Rt, and PEF. The functional networks is able predict water saturation with logarithm as the best selected basis function, achieving a root mean square error (RMSE) of 0.1143 and correlation coefficient (CC) of 0.9491 for the training set, RMSE of 0.0805 and CC of 0.9743 for the testing set. The result for the estimation is shown in the scatter plot for the best selected model from the basis functions. The plot also shows that there is a good matching between the core and estimated water saturation. Equation (13) shows the relationship between the predictor variable and the water saturation for the best selected model.

Comparison to artificial neural networks models

Artificial neural networks models were also developed in order to compare with functional networks. A feedforward multilayer perceptron neural network (FFNN) model trained with Levenberg Marquardt learning algorithm was used. A final model of 1 hidden layer of 5 neurons with tan-sigmoid and log-sigmoid at the output layer was realized in the estimation of porosity while 1 hidden layer of 10 neurons with tan-sigmoid and log-sigmoid at the output layer is realized in the estimation of water saturation. These networks are realized after a series of trial and error approach in selecting the number of hidden layer and number of nodes. The networks were trained for 500 epochs. The scatter plot of estimation of porosity and water saturation respectively.

The FFNN model predicted porosity with RMSE of 0.0245 and correlation coefficient of 0.93563 during training and RMSE of 0.0264 with correlation coefficient of 0.92594 during testing. FFNN model prediction for water saturation gives RMSE of 0.0436 with correlation coefficient of 0.9916 during training and RMSE of 0.0556 with correlation coefficient of 0.9884 during testing.

In comparison, functional network model performance is slightly better in the estimation of porosity, while neural network show slightly better performance to functional network in the prediction of water saturation. However, the long time taken to achieve the above neural network model topology can not be over emphasized. This is due to the well known problem of neural networks where a number of parameter has to be determined through trial and error. Another important advantage of FN over FFNN is that, FN provides insight into the network – gives the input-output relationship. For example, we can deduce from that the first three inputs have significant contribution to the network while (15) shows that the first four inputs have significant contribution for the prediction of water saturation. Aside these, FN has also demonstrated to be cost effective in implementation as it has lower network weights (N. weight) and execution time (Ex. Time) compare to FFNN.

DISCUSSION AND CONCLUSION

- In this study, we propose an alternative approach, functional networks, which provide a satisfactory prediction for reservoir porosity and water saturation from convectional well log. A simplified generalized functional networks model is learned and tested on combination of data sets from two wells. Different basis functions are used on the model and minimum description length was used to determine the best basis function to use for the problem. The results show that functional networks successfully predicted formation porosity and water saturation with low error and high correlation coefficients.
- A clear advantage of this technique over neural networks is the quick and unique solution obtained from the model. Another important advantage is that it discovers the relationship that exists between the predictor variables and the output. This provides valuable information about the variables, making it easy to know their significant as well as to compare with existing empirical or theoretical models.

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