Reservoir Porosity Prediction from Well Logs Using Neural Networks

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Abstract:

This paper presents neural networks (NN) model for one of the heterogeneous carbonate reservoir in the south of Iraq.

Because of complexity of carbonate rock (Mishrif formation/South of Iraq), porosity can be identified as a complex function of many independent parameters. The ideal results are not expected by using conventional techniques with log analysis, therefore, using the new technique utilizing neural network (NN) model included here to obtain more reliable results.

In order to create this model, there are three-layer back propagation network should be followed. Initially Gamma ray (GR), Spontaneous potential (SP), Neutron, Density, Sonic, and Resistivity were applied as input data. Optimization between the estimated and measured porosity from core analysis is reached, and finally, the results has been compared and showed that the accuracy of the model has been improved.

The porosity NN is executed by MATLAB(8.6), with log analysis as input data for one cored well ,Tuba-5. The data for this well was used for training and subsequently prediction and verification was done on the same well. However, porosity was estimated from conventional well logs using intelligent technique (neural network), and this technique is more accurate and reliable for estimating reservoir porosity compared with classical methods.

Keywords: Neural network, porosity prediction, well log.

Introduction:

Neural Networks method is commonly increased with reservoir characterization application. It is often useful where no simple mathematical relationship exists for the parameters of interest.

A neural network is approximation appliance that reconstructs a function based on limited set of dispersed data [2].

Many papers were presented to demonstrate the implementations of using the neural techniques in the oil reservoirs [3, 4, 5, 8,9,10, 11, &12]. Most of these implementations concern on one of the reservoir property such as porosity or permeability and identified it as a complex function for several interrelated parameters.

Neural Network (NN) method is a framework of several processing units known as neurons or nodes and these nodes or neurons are arranged in layers. Then the output of this network is subtracted from the actual output (real output data) of the problem. After that the resulting error is transported through the NN model and modifying the weights. This process which is called "training" should be continuous until the network output achieved reasonable values with actual or desired output values [1&7].

The amount of data which required to a reasonable system representation will increase proportionally with complexity of the system. i.e. the number of independent variables required for modeling a system is indication of the system complexity, then the instances number of the systems will be directly proportional to the number of variables.

Reservoir characterization is a process that used for identifying the various reservoir properties. However, for an un-cored depths and wells ,thereservoir characterization methods utilizing well log analysis represent an important technical and economical aspects cause well logs can supply a continuous record for the entire well when core samples are not possible.

Reservoir characteristics used all the obtainable data such as core analysis data, well logs, production history data and seismic, as well as reservoir characteristics include the distribution of grain size and facies, deposinal environment, lithology, permeability and porosity.

The indirect information about reservoir fluid content can be provided from well log data and there are several relationships relating the porosity with wireline log data such as neutron, sonic and density logs.

porosity is the key variable in evaluating the hydrocarbon accumulation in a reservoir. There is a transformation from neutron, density and transit time to calculate the porosity. this transformation formula contain expressions and factors that related with the individual location and lithology. e.q. shale content, fluid type, density and transit time of the grain, that in general are not known and must be estimated from core analysis [4].

Methodology:

In this study, a back propagation feed forward network ,i.e. the new technique was used as results of poor relationship between well log data and measured reservoir porosity from core samples.

Least Mean Square (LMS) that developed by Widrow and Hoff (1960) was the first linear adaptive-filtering algorithm for solving problems such as prediction.

Newton method is used to find the optimized wieght vector. Then adaption can be reached by using the least mean square method to find the wieght vector for the new input data, i.e. LMS-adapter can be used as a linear regression method to improve the processing between the elected well logs and core data.

The following steps was followed to create the new model:

- Multi input- single output of the unknown dynamic system was designed and built around a single linear neuron.
- Filtering and adaptive processes comprise a feed back loop acting around the neuron. Since the neuron is linear

$$y\,(i) = v(i) = \sum_{k=1}^{M} W_k(i)\, X_k(i) \quad (1)$$

$$y\,(i) = W^T(i)\, X(i) \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

where;

$$W\,(i) = [W_1(i), W_2(i), \ldots\ldots\ldots W_M(i)]^T$$

The error signal $e(i) = d(i) - y(i)$ is determined by the cost function used to drive the adaptive filtering algorithm, which is closely related to optimization process.

- The idea of using Newton's oral for optimization is to reduce the quadratic approximation of the cost function around the certain point.

Application:

Porosity has an important effect on a hyrocarbone reservoir operation and management and the reliability of reservoir geological model is primary depend on the accurate of interpolated petrophysical variables and the amount and scale of interwell variations of input data.

For an uncored depths and well of non-homogeneous reservoir, porosity determination using classic interpolation techniques is not always accurate. Therefore, an intelligent technique using neural network was suggested to determine porosity for Mishrif formation (carbonate reservoir) /Tuba Oil field in southern Iraq, Fig.1.

More than 30 wells were drilled in this reservoir, Fig. 2. Log data for most of these wells are available and just two wells (Tu-4 and Tu-5) have a core data as well as log data.

Tu-5 has a complete data of log records, table.1

, while well Tu-4 no data available about density records, therefore, the well Tu-5 was selected to create NN model.

Neural network was performed by problem definition, data pre-processing, training of network, verification and prediction. However the new intelligent technique using adapter- LMS was applied to the well data of Tu-5 well/ Mishrif fm./ Tuba Oil Field. One hundred fourteen core porosity values were measured for this well.

Neutron log, Sonic log, gamma ray log, resistivity logs (LLD,ILD, ILM, LLS) density log (RHOB), &spontaneous potential log were considered as a conventional well logs for analyzing and considered as interrelated (independent) data, as shown in **Fig.3**.

A cross plot between the porosities from well logs and core samples was constructed, and a poor relationship was found between them as shown in **Fig. 4**.

The first step is to select the best related logs data with measured porosity from core samples.

Phicore= f(GR, DT, NPHI, RHOB, ,SP, ILD, ILM,LLD,& LLS)

Next, a new optimization technique was used to analyze the correlation between variables for getting the reliable calculated porosity depending on input well log data. **Figs.5 & 6**.

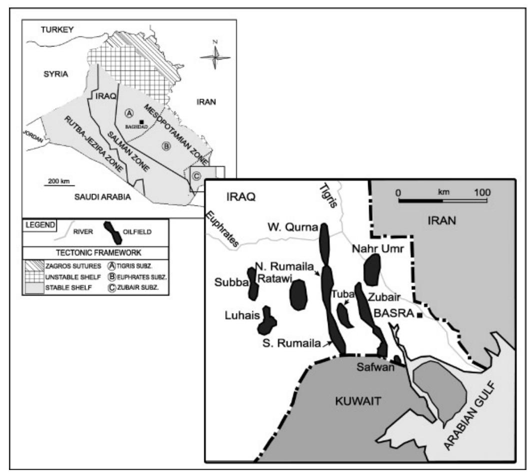

Fig.1 Location map of Tuba oil field

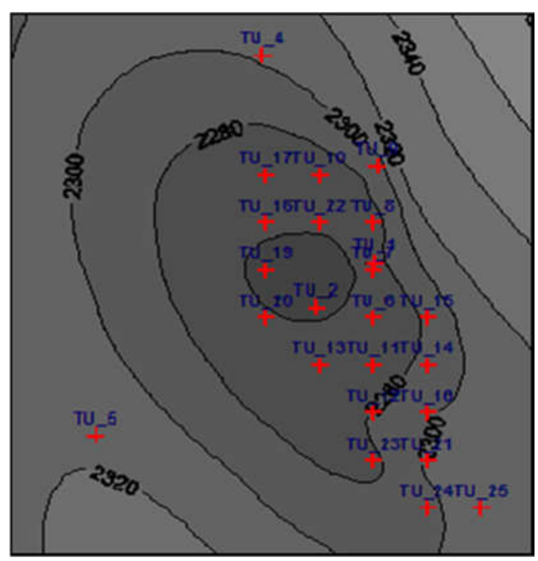

Fig.2 Well locations map field

Table.1. selected records of core porosity and well logs data,tu-5, for different levels

PHICORE perc.	GR api	DT uSec/ft	ILD ohm.m	ILM ohm-M	LLD ohm.m	LLS ohm-M	NPHI dec	RHOB gm/cc	SP mV
0.144	10.1895	66.856	1.15	1.39	2.5552	3.0982	0.1494	2.4766	12.4734
0.175	8.9707	70.402	1.27	1.46	2.4938	3.1118	0.1909	2.4075	12.1323
0.172	8.4551	68.137	1.83	1.94	3.0509	3.9016	0.1276	2.4519	12.3955
0.102	9.8848	63.254	2.545	3.215	7.1966	8.4998	0.1089	2.5339	10.1801
0.168	6.8718	67.9725	2.745	2.99	5.7525	5.5457	0.1607	2.4288	11.7655
0.121	7.0437	67.527	2.26	2.59	5.1372	5.4874	0.1532	2.4443	12.9159
0.082	6.8601	69.137	2.09	2.19	4.6479	4.3592	0.1461	2.4543	13.0159
0.125	7.8679	64.383	2.69	2.9	6.9393	5.5218	0.116	2.5144	13.0604
0.175	6.0242	62.121	3.92	4.52	9.9751	9.1151	0.1223	2.5177	11.6171
0.187	8.7051	66.324	4.04	4.52	6.798	8.5096	0.1408	2.459	9.4022
0.049	4.7924	69.871	2.97	2.695	5.7602	3.8717	0.1775	2.3862	8.5652
0.083	6.0281	74.215	2.75	2.84	3.0864	3.5697	0.1818	2.372	9.4394
0.066	7.6667	65.4805	1.185	1.44	4.6757	3.1269	0.1437	2.4569	12.0645
0.067	4.5867	72.824	0.83	1.09	2.7405	2.3679	0.1921	2.3732	9.6292

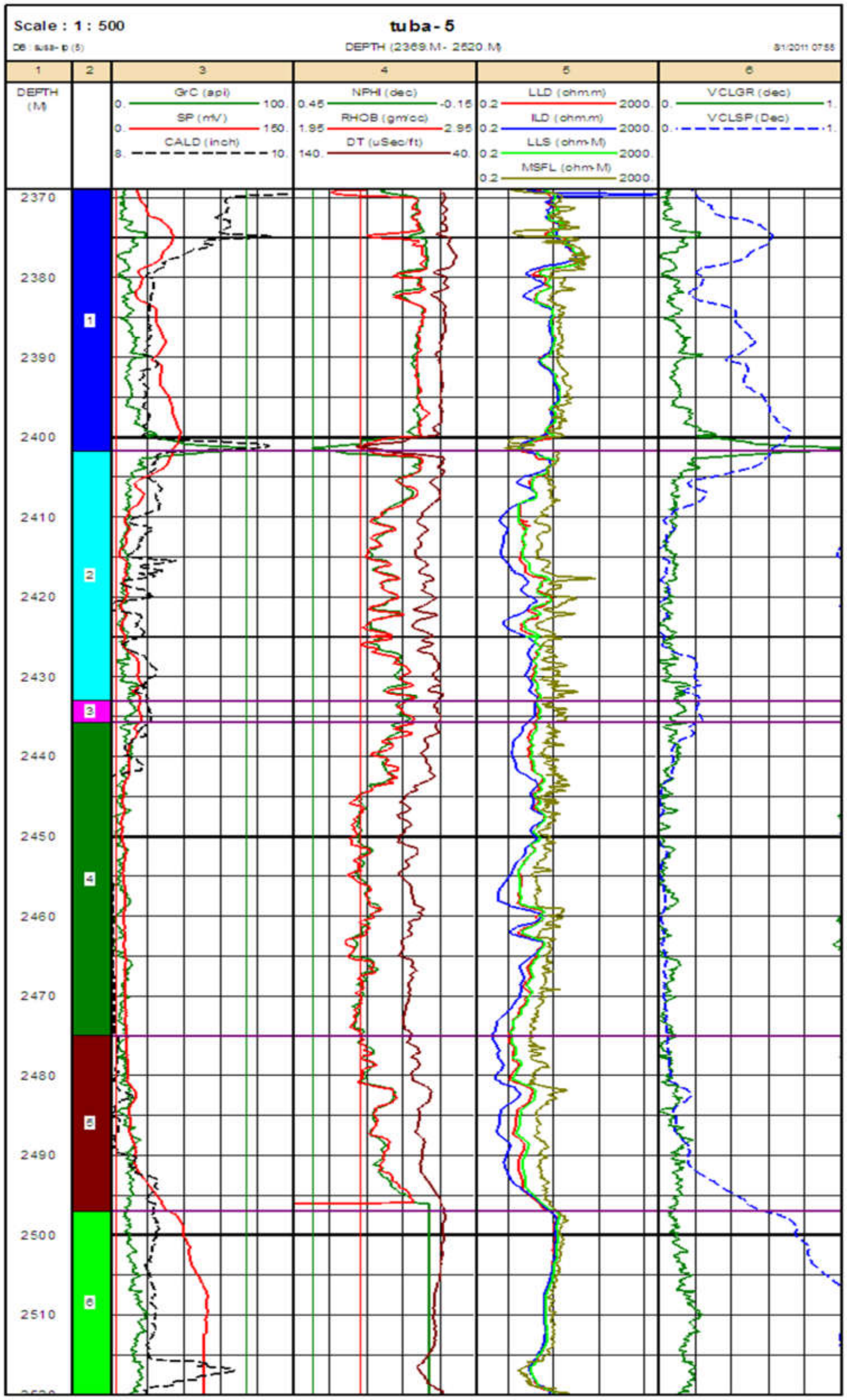

Fig.3 Well log data for TU-5.

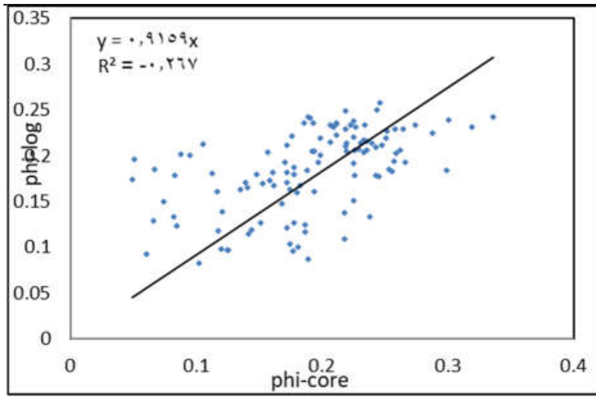

Fig.4. Relationship between core porosity and log porosity

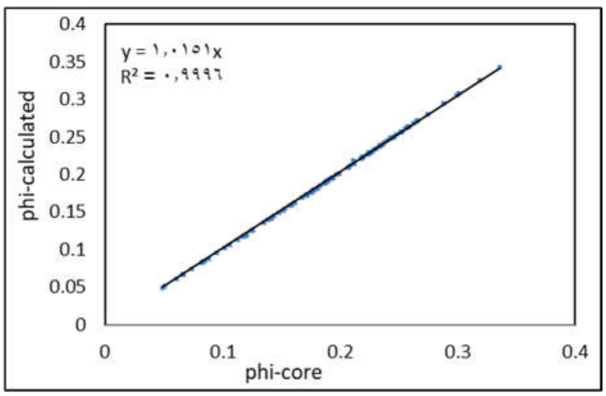

Fig. 5. Relationship between core porosity and NN porosity

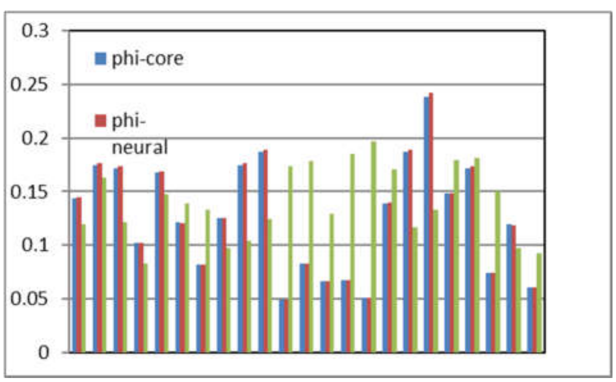

Fig.6. Histogram of core porosity compared with porosity from well log and NN methods

Conclusions:

- The estimated porosity using conventional well log method shows inaccurate results compared with measured data from core analysis for carbonate reservoir which is strongly heterogeneous.
- Adapter - LMS technique was used to select the best dependent parameters with reservoir porosity.
- The proposed neural network approach was applied as a appliance to predict reservoir porosity for non-homogeneous reservoir using the data of well log.
- The porosity values that estimated from the new approach (NN) show an accurate and reliable results compared with those from well log analysis.

Nomenclature:

GR : GammaRay 3 Uranium-Free Gamma Ray, .Api.
DT : Acoustic Transit Time, .uSec/ft.
ILD : Deep Induction, .ohm.m.
ILM : Medium Induction, .ohm-M
LLD : Laterolog, .ohm.m
LLS : Shallow Laterolog, ohm-M
NPHI : Compensated Neutron Porosity, .dec .
phicore : Core porosity , dec.
RHOB : Density, .gm/cc
SP : Spontaneous Potential, .mV

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التنبؤ بالمسامية من تسجيلات الابار باستخدام الشبكات العصبية

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الخلاصة:

يعرض في هذا البحث عمل نموذج من الشبكات العصبيةلأحد المكامن الكربونية الغير متجانسة في جنوب العراق.
وبسبب التعقيد في الصخور الكاربونية (تكوين المشرف/ جنوب العراق)، فإنه من الممكن توصيف المسامية على انها دالة معقدة للعديد من العوامل المستقلة. النتائج المثالية غير متوقعة باستخدام التقنيات التقليدية مع تحليل تسجيل الابار، وبالتالي، باستخدام تقنية جديدةبواسطة نموذج الشبكة العصبية المدرجة هنا يمكن الحصول على نتائج أكثر موثوقية.

هناك ثلاثة طبقات من شبكة الانتشار الخلفي (back propagation) لإنشاء هذا النموذج. في البداية تم تطبيق (GR, SP, Neutron, Density, Sonic, and Resistivity) كبيانات مدخلة. وقد تم التوصل إلى التحسين بين المسامية المقدرة والمقاسة من تحليل النموذج الصخري ، وأخيرا تمت مقارنة النتائج وأظهرت أن دقة هذاالنموذج قد تحسنت.

المسامية المقدرة من الخلايا العصبية (NN)اهو نموذج بسيط يتم تنفيذه من قبل برنامج ماتلاب (8.6)، مع تحليل سجل البئر كبيانات مدخلة لبئر ماخوذ منه نماذج صخرية، بئر(tu-5) واستخدمت البيانات الخاصة بهذا البئر من أجل التدريب، وبعد ذلك جرى التنبؤ والتحقق على نفس البئر. وعلى كل حال فان مساميةالمكمن قد تم تقديرها باستخدام تقنية ذكية (الشبكة العصبية)وبالاعتماد على بيانات التسجيل البئري التقليدي، وهذه التقنية يمكن أن تجعل تقدير مسامية خزان النفطي (المكمن) أكثر موثوقية ودقة مقارنة مع الطرق التقليدية.

الكلمات المفتاحية:- الشبكة العصبية، التنبؤ بالمسامية، تسجيل الابار.