New models for prediction of reservoir rock properties in Biyad formation of Kharir oil field, Hadramout Governorate

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Abstract

Reservoir description is a process of describing various reservoir characteristics using all the available data. The nature of the description of reservoir properties is related to the availability of sample data and geologic complexity of reservoir. Reservoir characterization is needed for effective reservoir management studies. Reservoir rock properties can be estimated by several methods. Rock properties are determined by performing laboratory analyses on cores extracted from the reservoir. However, obtaining the properties from core analysis or well logging is time consuming and an expensive operation. For that, in this work, new models for estimating rock properties (porosity, permeability) are developed by adapting Artificial Neural network model (ANN). Models were successfully demonstrated for predicting reservoir rock properties (porosity and permeability) forBiyad formation of Kharir oil field. The models were tested against properties yielded from core laboratories using statistical error analysis. Result showed a great potential in predicting reservoir properties using artificial intelligence models.

Keywords: new model, neural network,rock properties, Kharir oil field, Biyad formation, Hadramout Governorate.

Introduction

The knowledge of petrophysical properties of reservoir rocks has a fundamental importance to the petroleum engineer. Reservoir characterization plays an important role in the reservoir management process. The quantity of recoverable petroleum in a reservoir and the rate at which it can be produced depend primarily on the properties of the reservoir rock and the fluids saturation. These data are obtained from two major sources: core samples analysis and well logging.

The properties of reservoir rock (porosity and permeability) can be estimated by using laboratory methods or from geophysical well logs, often called wireline well logs. This method of porosity evaluation is not very accurate, but has the advantage of providing continuous porosity data. Once these logs are obtained and converted into a porosity log, they can be calibrated using core-sample porosity data and serve as additional reliable source of porosity distribution evaluation. Porosity can be estimated from Formation resistivity factor F; Micro Resistivity log; Neutron - gamma log; Density log; Acoustic (sonic) log. Well test analysis provides information on reservoir description, reservoir heterogeneities and permeability[2,3,12].

Rock properties are also determined by performing laboratory analyses on cores from the reservoir to be evaluated. The cores are removed from the reservoir environment, with subsequent changes in the core bulk volume, pore volume, reservoir fluid saturations and, sometimes, formation wettability. In this paper, a modeling approach for reservoir properties determination is introduced.Developed models are demonstrated on estimating rock properties (porosity, permeability) for Biyad formation of Khariroil field.

Geology of Kharir field

The Biyad formation of Kharirfield is located in the production license block 10 (East Shabwa) in Yemen, two separated structures are identified (Figure.1):

1. The main structure, located in the southern part, is a faulted anticline trending WNW-ESE. This structure is divided into two compartments based on pressure data:

• The southern compartment (Kharir–1 / K1 compartment), including one oil producer well (Kha-101).

• The northern compartment (Kharir-2 / K2 compartment), including six oil producer wells (Kha-201, 202, 203, 204, 205and 206) and three water injection wells (Kha-211, 212 and 213). The wells are oil-bearing in the Upper Biyad formation only.

2. The second structure (K3 compartment), located to the north of K2, includes five oil producer wells (Kha-301, 302, 303, 304, 305) and one water injector well (KHA306). This structure corresponds to an isolated NW-SE oriented anticline. The oil-bearing reservoirs include both Upper, Lower Biyad and Sarr formations.

The well Kha-102 is located in the eastern part of the K1 compartment. It was drilled to drain the Upper Biyad oil bearing layers in a high structural position close to the K1 compartment limiting fault. Figure 1 Shows East-Shabwa Block 10 fields and prospects andFigure2 shows the Kharir top upper Biyad depth map.

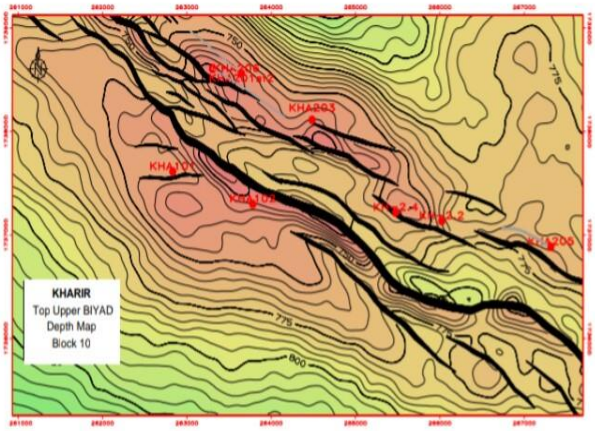

Figure 1: Kharirtop upper Biyad depth map

Well Objectives

The main objective of the Kharir-102 vertical well is to appraise the Upper and Lower Biyad, Sarr and Basement reservoirs. Basement penetration was anticipated to be at least 100m with 60° inclinations. In case of negative results in the Basement, an optional sidetrack, with an 800m drain length in the Upper Biyad, was included.

The secondary objectives are to calibrate and to appraise the Upper and Lower Biyad, Sarr and Basement reservoirs in the K1 compartment.In case of oil shown in the Basement, production tests were programmed. The production is highly dependent on the fracture system encountered. To enhance the chances of crossing fractures, the well trajectory was in the N15° azimuth perpendicular to the main fault system azimuth (N120°) with 60° inclinations.

The Sarr reservoir and the Lower Biyad were encountered water bearing in the K1 compartment. However, an important structural column remained to be appraised. In case of bad reservoir results in the Basement, Sarr and Lower Biyad, a test was planned in the Upper Biyad.To increase the oil production rate (2000 bops for a vertical well), a sidetrack was proposed with a drain length of 800m leading to a potential initial production of 5500 bops.

Structure

The initial objective of Kha-102 is to drain the untapped oil in the Upper Biyad layers in an up-dip position from the Kha-101. Kha102 well was planned to enter the Upper Biyad reservoir at -732 m/MSL, 15m higher than KHA101 well at -746.9 m/MSL). However, the Upper Biyad was encountered in Kha-102 at a slightly higher structural position than expected at -730.1 m/MSL. After the 9 5/8" casing, set at 2405m, a FMI was performed from 2405 to 2547m. The formation dips correspond to 10° to the SSW perpendicular to the well profile.

The Basement was expected at -1334 m/MSL and tagged in deeper structural position at -1334 m/MSL.As the Basement corresponds to a paleo relief, the Shuqra thickness is variable (62.8m in Kha-101 and only 13.3m in Kha102). Idem for the Haifa formation was deposed on the Madbi discordance with a drilled thickness less than in Kha-101 (41.9m in Kha-101 and 7.1m in Kha-102). Due to these discordance and paleo relief, the top Basement was difficult to predict while drilling.Compartment limiting fault: the main K1 compartment limiting fault dipping approximately 60° southwards was encountered at 1280m MD / -281.4 m/MSL, while drilling the Harshiyat formation. No indication of the throw is available.

The Regional lithostratigraphy for Kharir field is displayedin Figure 3. Structural formation dips: from a geometrical layering interpretation, the structure correspond to a monocline slightly dipping SSW. According to the dips from the FMI interpretation, the structure is dipping from 5 to 10° with a main azimuth towards the SSW. Locally, in the Madbi limestone, 20 to 30° dip are observed. The FMI was only run in the Madbi and Shuqra formations (Jurassic sin-rift deposits), and the pre-Portland tectonic probably affects the formation dips. The dips from the post rift overlying formations are anticipated to be less but no FMI data confirms this in the well. Figure 3 shows the Kharirtop SARR depth map.

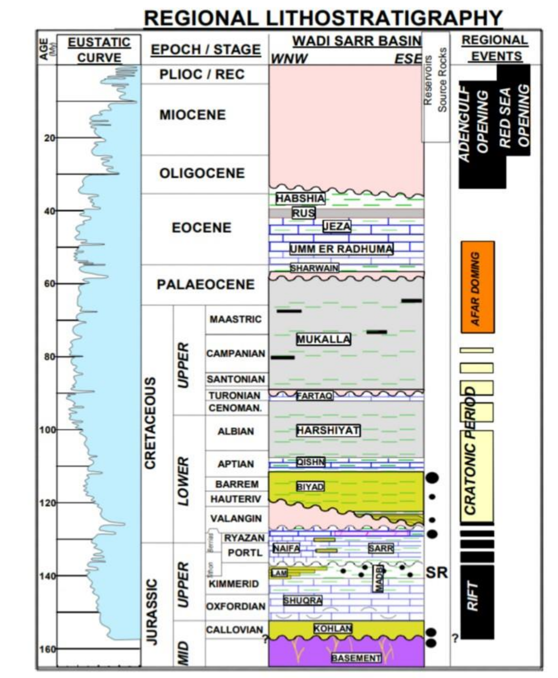

Figure 3: Regional lithostratigraphy

Available Data

Different log typesfrom four wells(well Kh-102,(Kha-301,Kha-302 and Kha-303)are used in this study. They include: Gamma ray (GR), Resistivity log, Deep, Shallow, Micro, Density log (RHOB), Formation Bulk Density log), Sonic log (BHC, Borehole compensated sonic log), and Neutron porosity log (NL), Neutron porosity log. These logs were converted to digital format for each meter.

Research Methodology

To achieve the objectives of this study, first equations are used to interpret well logsand determine the main rock properties. Excel sheet is developed for this purpose.

Building new neural network model for predicting reservoir properties were conducted using software program. The collected field data were randomly divided into three parts. The first was used to train the model, the second to validate, and the third part for testing the performance of the model.Finally,model evaluation was conducted by comparing the results obtained from the model with actual values of core samples using statistical error analysis.

Artificial Neural Network

Artificial neural networks (ANN) have been involved in many applications to solve real world problems. In petroleum, engineering ANNs can be applied to solve many engineering problems such as classifications, prediction and pattern recognition. Neural networks have been utilized to predict the formation characteristics such as porosity and permeability from conventional well logs [1, 4, 10, 11]. Using well logs as input data coupled with core analysis of the corresponding depth, these reservoir characteristics were successfully predicted for a heterogeneous formation in different areas [7,8].

New ANN Model for the Prediction of Permeability and Porosity

Based in the real Kharir field data,AlyudaNeuroIntelligence software program is used to build new model of artificial neural networks (ANN) which can estimate the desired porosity and permeabilityfrom real input data acquired from Kharir oil field.

Building the Model

Data sets obtained from the Kharir oil field were used to build model for prediction the reservoir properties (permeability and porosity). A total number of 96 data points with wide range variety of all parametersgamma ray log(GR), $_{bulk}$ density log (RHOB), neutron porosity log (NPHI), sonic log

(DT), lateral log deep (LLD), and micro resistivity log (MSFL).Table 1 presents the description of data utilized in this study.

Table 1: Range of parameters for porosity

Parameter	Maximum	Minimum	Average
GRapi	91.4455	9.6533	30.16129
RHOB g/cm^3	2.6964	2.1305	2.442258
NPHI%	0.4666	0.0209	0.181081
DTus/ft	111.7549	59.1906	76.18771
LLDohm	169.3306	8.4258	44.09279
MSFLohm	284.3333	2.1963	29.75296

The input parameters to model for porosity are GR, RHOB, NPHI, DT, LLD, and MSFL, and the input parameters to model for permeability areGR, RHOB, LLD, and NPHI. Permeability and porosity were used as an output parameter. Data wererandomly partitioned. Data Partition means division of each dataset onto three sets: the training set, the validation set and the test set [5].

The Training set is a part of input dataset used for neural network training, i.e. for adjustment of network weights. The validation set is a part of the data used to tune network topology or network parameters other than weights, for example, the number of hidden units. Validation set is used to calculate generalization loss and retain the best network (the network with the lowest error on validation set). About 65 records were randomly distributed to (70 %) of data to training set, 14 records (15%) to validation set and 14 records (15 %) to test the model for porosity; and About 61 records randomly distributed to (70 %) of data to training set, 14 records (15%) to validation set and 14 records (15 %) to test the model for permeability. Neural network Architecture (input layer and number of neurons, hidden layer and number of neurons in hidden layer) was selected manually. Hidden layers' activation, Error function and activation function were also specified. Data preprocessed using scaling range: (-1,1) for input parameters. Output variable was transformed to a scale between 0 and 1. The network training is accomplished by Quasi-Newton algorithm for both models.

The network is trained by iteration process. When the desired network error on the training set is lower than specified, the training will be stopped.

Overtraining is identified using the validation set. The situation that the network error increases on the validation set during several iterations, while still decreasing on the Training set is identified as the starting point of overtraining. Neural network was automatically tested after Training completion. In the testing process, the actual porosity vs. output porosity and the actual permeability vs. output permeability were compared. Error values for each data point from the input dataset were calculated.

Search the Optimal Network Architecture

The logistic search method is used to finding optimal neural network architectures and to find the number of nodes in the input; hidden layers were done according to a maximum fitness function (minimum training error). The neural network model consists of three layers: input layer, hidden layer, and output layer. Figure 4 and Figure 5 show schematic of developed ANN models forthe prediction porosity and permeability respectively.

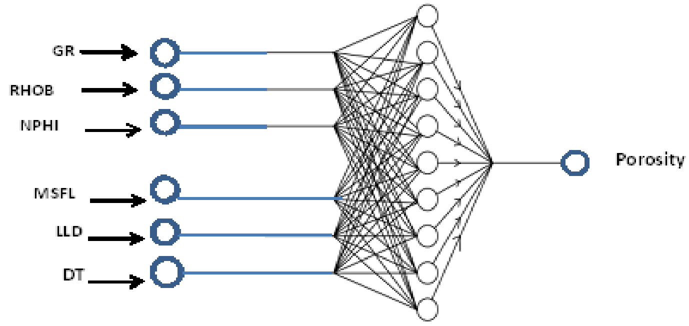

Figure 4: schematic of developed ANN model for porosity

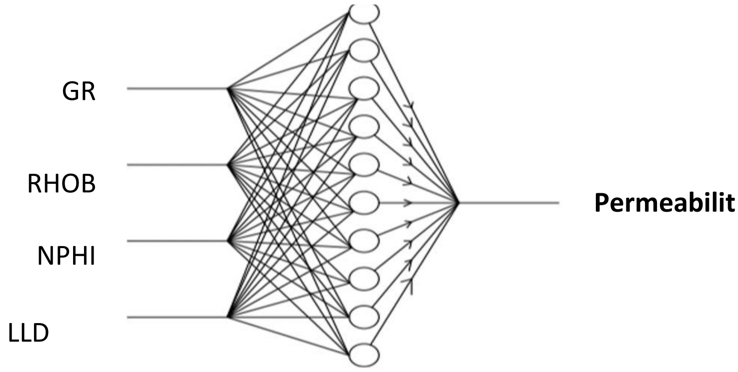

Figure 5: Schematic of developed ANN model for permeability

Smaller test error gives the better network. This parameter is calculated as inverse mean absolute network error on the test set. Logistic search method along the architecture search and training by Quasi-Newton [6,8] for both models were used. Table 2 shows the best architectures of input data for porosity model and permeability. As shown from Table 2, the best architecture for porosity modelis (6-9-1). In addition, the best architectures for permeability model, the best architecture is (4-10-1).

Table 2: The best model architecture by R and network error for porosity

Architecture	R			Network Error
	Training	Validation	Testing	
Porosity				
(6-9-1)	1	0.997	0.999	**2E-7**
Permeability				
(4-10-1)	**1**	**0.999**	**0.998**	**3.2E-10**

Contribution of Input Parameters

Table 3 shows the importance of all input parameters used to build the new ANN model for porosity, the most important inputs data is **NPHI** with 37.42%, followed by **MSFL**with 25.75% and the ***GR*** is the lowest important with 1.8%.Table 4 shows the contribution of all input parameters used to build the new ANN model for permeability, the most important of inputs data is **GR** with 35.5%, followed by **NPHI**with 30.8%, and the **LLD** is the lowest important with 11.9%.

Table 3: Importance of each input parameter to build the model for porosity

Parameter	GR	RHOB	NPHI	MSFL	LLD	DT
Importance %	1.8	10.178	37.42	25.75	17	7.8

Table 4: Importance of each input parameter to build the model for permeability

Parameter	GR	RHOB	LLD	NPHI
Importance %	35.5	21.7	9.9	30.8

Results and Discussion

The developed ANNs were successfully trained and tested using the available data sets (training, validation, testing and all). The validity and performance of ANN models were determined by correlation coefficient (R), average percent error(APE), maximum error (MAX),minimum average error(MIN)absolute average percent error(AAPE)and standard deviation(STD). The best logarithm is Quasi-Newton for both models, the best architectures is (4-10-1) for permeability model, and the best architectures for porosity model is (6-9-1).

Table 5 presents the comparison between actual porosity and permeability and estimated porosity and permeability from new ANN model.

Table 5: Results of comparison between actual porosity and estimated porosity from new ANN model

Porosity					
APE	**AAPE**	**MAX**	**MIN**	**STD**	**R**
0.68	11.5	7.5	0	98	0.9993
Permeability					
8.6	12.45	69.5	0	15.6	0.998

Figures6 shows regression plot of the estimated porosity data from ANN model versus relevant core porosity data. The outputs of ANN model for training, testing, validation and phase have high accuracy in predicting reservoir porosity with stable performance. The output of the ANN is closed to correspond real core porosity values and to achieve correlation coefficient of 1 and 0.999 for training and testing data, respectively.

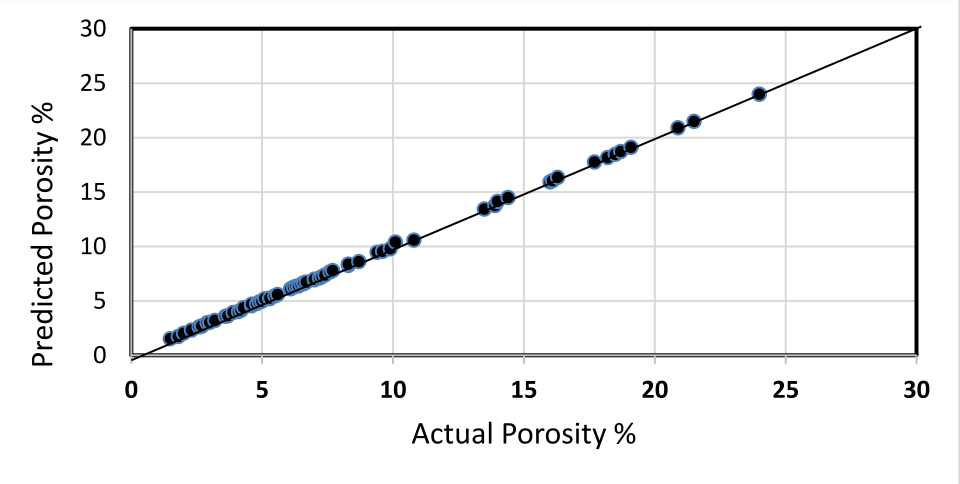

Figure 6: Cross plot of predicted porosityfrom ANN model and core porosity data (training data)

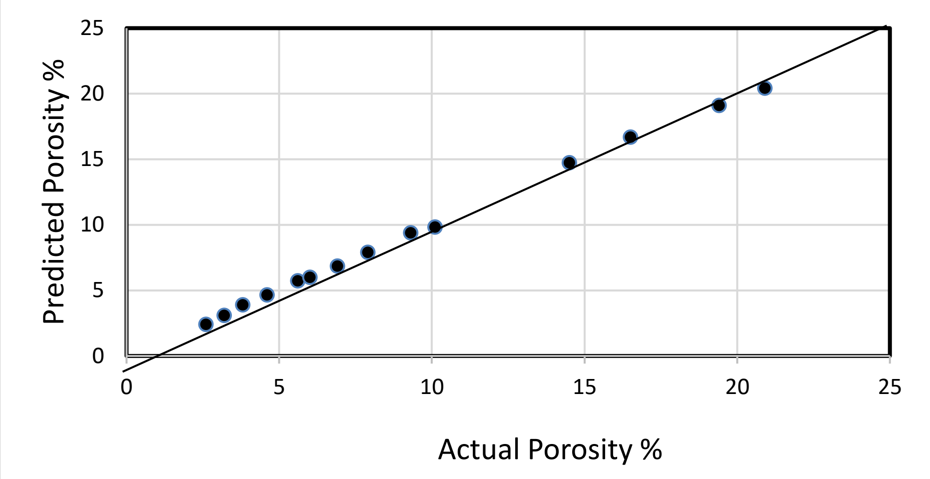

Figure 7: Cross plot of predicted porosityfrom ANN model and core porosity data. (testing data)

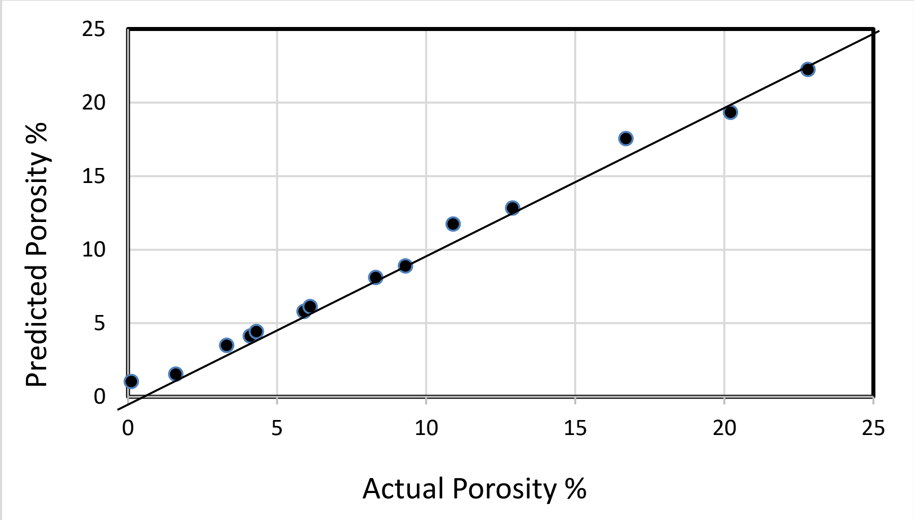

Figure 8: Cross plot of predicted porosityfrom ANN model and core porosity data(validation data)

Figure 9shows the scatter plot between actual porosity with the porosity predicted by the model. It is indicated that the accuracy of the results presented in this figure are very good, compared with the actual porosity.

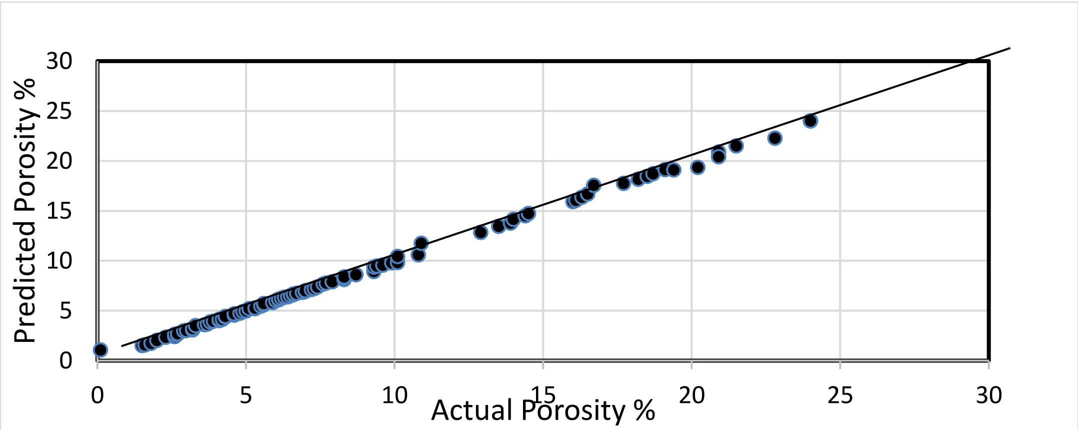

Figure 9: Scatter plot between actual data vs. predicted data from porosity model

Figure 10shows regression plot of the estimated permeability data from ANN model versus relevant core permeability data. The outputs of ANN model for training, testing, validation and phase have high accuracy in predicting reservoir permeability with stable performance.The output of the ANN is closed to correspond real core permeability values and to achieved correlation coefficient of 1 and 0.998 for training and testing data, respectively.

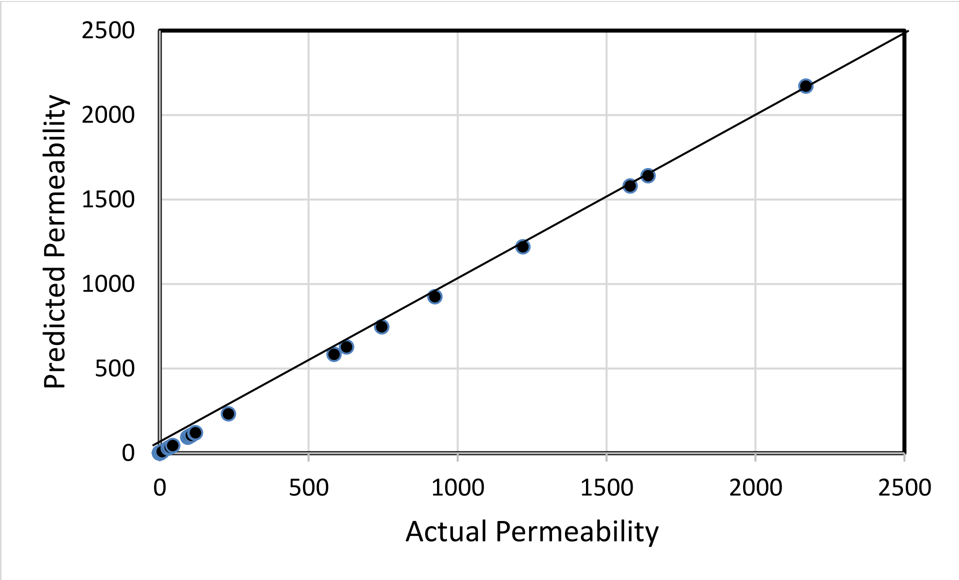

Figure 10: Crossplot of estimated permeability from ANN model and core permeability data. (Training data)

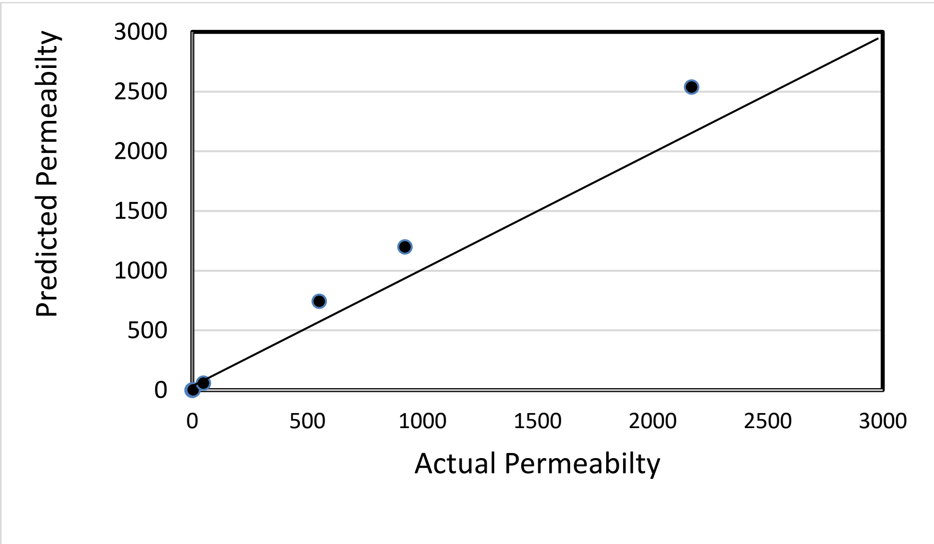

Figure 11: Crossplot of estimated permeability from ANN model and core permeability data. (Testing data)

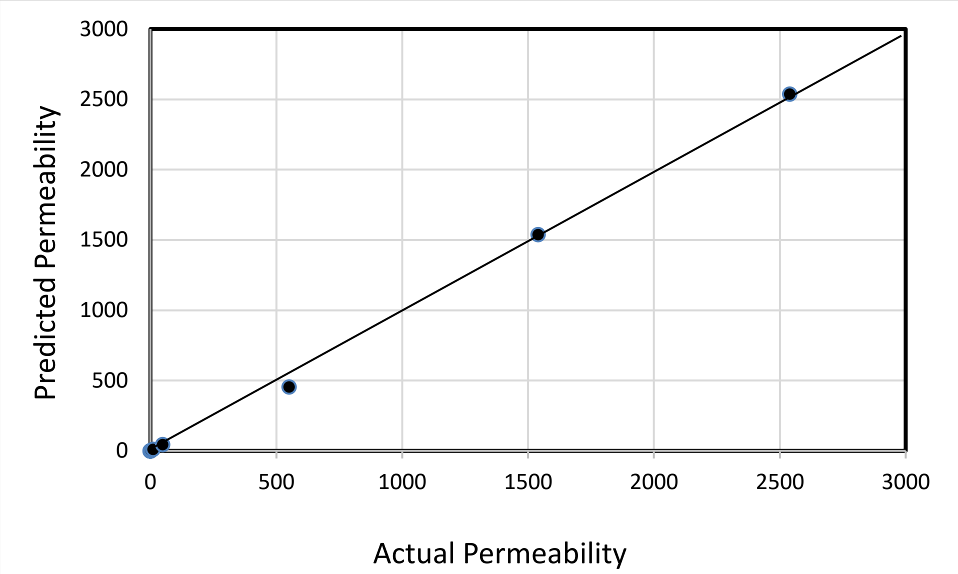

Figure 12: Crossplot of estimated permeability from ANN model and core permeability data. (Validation data)

Figure 13 shows the scatter plot between actual permeability with the permeability predicted by the model. It is indicated that the accuracy of the results presented in this figure are very good, compared with the actual permeability.

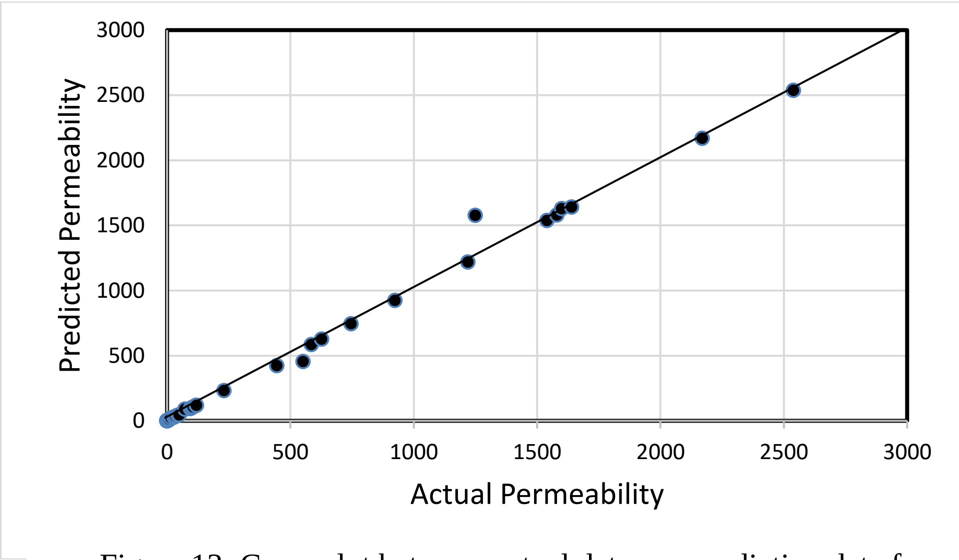

Figure 13: Cross plot between actual data vs. prediction data from

Table 6 and 7 show parameters output from the new model for porosity and permeability.

Table 6: Parameters resulted from the new model for porosity prediction

Parameters	**Training**	**Validation**	**Testing**
AAPR	0.857	70.7	1.99
R	1	0.997	0.999
STD	0.816	252.7	1.89
Architecture	(6-9-1)		
Algorithm	Quasi-Newton		

Table 7: Parameters resulted from the new model for permeability prediction

Parameters	**Training**	**Validation**	**Testing**
AAPR	10.9	13.12	18.4
R	1	0.999	0.998
STD	15.75	17.8	12.2
Architecture	(4-10-1)		
Algorithm	Quasi-Newton		

Application of New Model to Khariroil field

Ability of the proposed model to the prediction of porosity and permeability of Kharir oil field was examined. More than 95 data points that had been collected from Kharir oil field were used to test the new model. Table 8 shows that very good results are obtained with Artificial neural networks new model for porosity.

Table 8: Results of Statistical Analysis for new model for porosity using data from Kharir oil field

Porosity					
APE	**AAPE**	**MAX**	**MIN**	**STD**	**R**
0.68	11.5	7.5	0	98	0.999
Permeability					
8.6	12.45	69.5	0	15.6	0.998

Figure 14 shows the ability of new ANN to predict the porosity for Kharir oil field with excellent performance, with high agreement between actual porosity data and the corresponding neural network output porosity data.

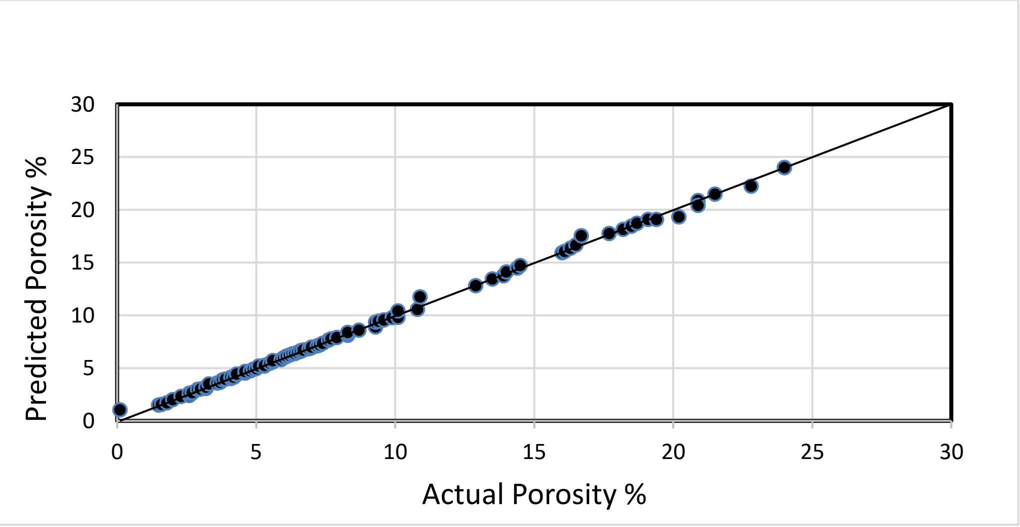

Figure 14: Scatter plot between actual data with ANN model outputs for porosity

Table 7shows that very good results are obtained with artificial neural networks new model for permeability.

Figure 12 shows the ability of new ANN to predict the permeability for Kharir oil field efficiently,with high agreement between actual permeability data and the corresponding neural network output permeability data.

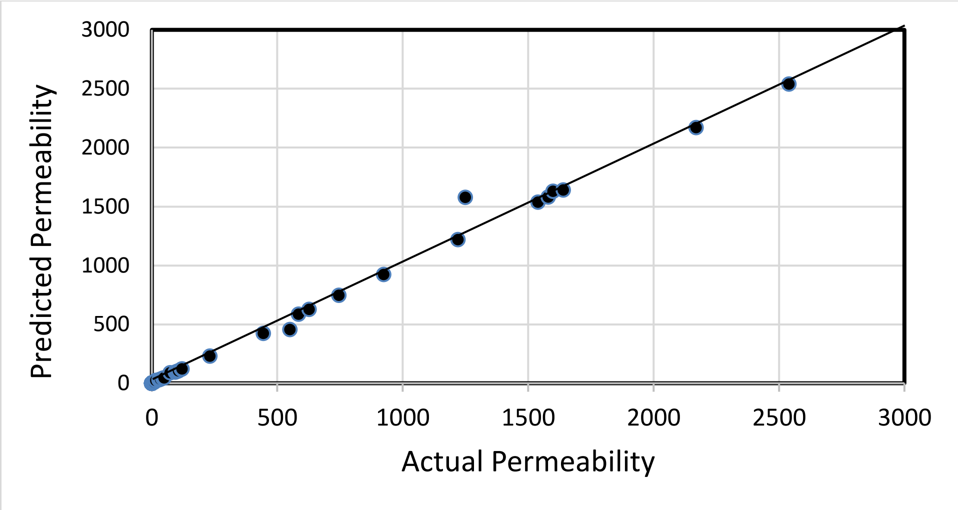

Figure 15: Cross plot between actual data with ANN model outputs for permeability

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نماذج جديدة للتنبؤ بخصائص صخر المكمن في تشكيل البياض لحقل خريرة النفطي- محافظة حضرموت

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الملخص

وصف المكمن هي عملية تصف خصائص المكمن المختلفة باستخدام جميع البيانات المتاحة والمتوفرة. ترتبط طبيعة وصف خصائص المكمن بتوافر بيانات عن العينات وبقية الخصائص الجيولوجية والتعقيدات الجيولوجية. وصف المكمن مهم للدراسات الفعالة لإدارة المكامن. يمكن تقدير خصائص صخور المكمن بعدة طرق. يتم تحديد خصائص الصخور المكمنية عن طريق إجراء تحاليل مختبرية على عينات الحفر اللبية المستخرجة من المكمن (core samples) وما يصاحبها من اختبارات موقعيه للحقل المقرر تقييمه. ومع ذلك، فإن عملية الحصول على الخصائص من تحليل العينات أو تسجيل الآبار تستغرق وقتًا طويلاً وتكلفة باهظة. لذلك في هذا البحث، تم اعتماد تطبيق نماذج جديدة لتقدير خصائص الصخور (المسامية، النفاذية) لتشكيلة بياض في حقل خرير النفطي- محافظة حضرموت. تشمل هذه النماذج نموذج الشبكات العصبية (ANN).

تم إثبات نجاح هذه النماذج للتنبؤ بخصائص صخور المكمن (المسامية والنفاذية) لتشكيلة بياض في حقل خرير. تم اختبار الموديلات مع الخصائص الناتجة من مختبرات تحليل العينات باستخدام تحليل الأخطاء الإحصائية، إذ أظهرت النتائج إمكانية كبيرة على التنبؤ بخواص المكمن باستخدام نماذج الذكاء الاصطناعي.

الكلمات المفتاحية: نموذج جديد، الشبكات العصبية، خواص الصخور، تشكيل بياض، حقل خرير النفطي، محافظة حضرموت.