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A fuzzy logic approach to infer reservoir permeability from depth and porosity measurements for Mishrif limestone Formation at Nasyria Oil Field, south of Iraq

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Abstract: This study explores the application of Takagi- Sugeno fuzzy inference system to predict reservoir permeability form depth and porosity measurements for Mashrif Formation in Nasyria Oil Field, south of Iraq. The models developed intend to describe the non-linear relationship between depth and porosity as inputs and permeability as output. A total of 206 core samples from three exploration wells (Ns-2, Ns-3, and Ns-5) were used to build a fuzzy model. Input data were divided into two groups including training set (170 data points) which represent the Ns-2 and Ns-3 wells; and testing set (36 data points which represent Ns-5). All membership functions and IF-THEN rules of the inference system were derived by using subtractive clustering technique. The performance of the model was measured by using degree of determination. The results of this study indicate that fuzzy logic technique is suitable to infer permeability from depth and porosity measurements alone without the need for the very expensive coring process. The calculated degree of determination was 0.98 for testing data set. A few core permeability and porosity measurements are required first to build fuzzy model and the fuzzy inference engine predict permeability for other sites of the field by knowing depth and porosity inputs which can be taken from conventional well logs data.

Key Words: fuzzy logic, Takagi-Sugeno fuzzy inference system, Mishrif Formation, Iraq

Introduction

Permeability is one of the most important properties of a reservoir formation. An accurate determination of this property provides geologist with a powerful tool for efficiently managing the production process of a field and helps to make a sound reservoir based decisions. Permeability also is an elusive property as it is very difficult to infer using current sub-surface logging. Generally, core measurements are the accurate technique to acquire permeability. Unfortunately, only few wells from any field is coring due to the fact that the coring is an expensive process and sometimes impossible especially for horizontal wells.

Basically there are three techniques being available to infer rock permeability: empirical relationships, statistical based methods, and artificial intelligent methods. Empirical relationships attempt to correlate permeability with other rock and fluid properties such as porosity, irreducible water saturation, pore throat, grain sizes, facies, sedimentary structures, formation resistivity factors, sonic transit time, capillary pressure etc. The main drawback of these techniques is they require a labor intensive exercise to adjust constants or exponents [1]. Sometimes core permeability data are available for most exploration and development wells, hence statistical based techniques have becomes a more versatile alternative in solving the problem of determining reservoir permeability [2]. Regression analysis is the most widely used statistical technique in oil industry. In regression analysis it is assumed that the a known linear or non-linear function is sufficient for modeling the relationship between the dependent variable (Permeability) and the independent variables (other rock properties such as porosity). Unfortunately, the technique requires the assumption and satisfaction of multi-normal behavior and linearity in case of multivariate linear regression, and must be applied with caution [3]. Beside statistical methods, intelligent systems such as artificial neural network, fuzzy logic, and genetic algorithm have been used as a tool for modeling and prediction in the reservoir studies. The main advantage of these techniques are 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. Several studies have been carried out for the estimation of reservoir parameters by intelligent systems (e.g. [4] [5] [6] [7] [8] [9] [10] [11] [12] [13] [14] [15] [16] and [17]). The results show that these techniques are powerful, inexpensive and easy for constructing models. With respect to permeability prediction, Shokir et al [2] presented a non-parametric model to predict reservoir permeability from conventional well log data using artificial neural networks. They concluded that the ANN model was a powerful tool for permeability prediction from well log data. Saemi and Ahmadi [4] introduced a new hybrid network based on coactive neuro-fuzzy inference system to predict reservoir permeability. Their study showed that using the proposed methodology able to infer rock permeability with accuracies comparable with actual laboratory core measurements for the location that core samples are unavailable. Rezaee et al [6] used a fully- connected ANN to predict permeability from porosity and pore throat radii. Their results indicated that pore throat radius at 50% mercury saturation yields the best correlation coefficient for permeability, porosity, and pore throat radii for carbonate rocks. Ilkechi et al [7] presented a methodology for the estimation of permeability and rock type in the Kangan Formation in the Iran offshore gas field by using fuzzy inference system. Their study results indicated that fuzzy logic model is an instruments tool for the permeability and the identification of permeability and non-permeable zones in the Kangan Formation. Lim [9] suggested an intelligent technique using fuzzy logic and neural network to determine reservoir properties from well logs. The main conclusion of his study demonstrated that these techniques could be utilized as a powerful tool for reservoir properties estimation from well logs in oil and natural gas developed projects.

The main focus of this paper is to use intelligent fuzzy inference system to build a relationship between depth, porosity, and permeability for the Mishrif limestone formation in Nasriya oil field, south of Iraq, and uses this relationship in a predictive sense.

Fuzzy Logic

Fuzzy logic is based on the theory of fuzzy sets which relates to classes of objects without sharp boundaries in which membership is a matter of degree. In this approach, the classical notation of binary membership in a set has been modified to include partial membership ranging between 0 and 1 [18]. A member shape function (MF) is a curve that defines how each point in the input space is mapped to a membership value. There are several types of membership shapes (Fig.1) being used. The generation of a fuzzy model can be based on expert knowledge and historical data. Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made or discerned. Basically, fuzzy logic system has four components: (Fig.2)

1. Fuzzification: is the process of decomposing a system input and/or output into one or more fuzzy sets.
2. Fuzzy rules: IF-THEN rule statements are used to formulate the conditional statements that comprise fuzzy logic. A single fuzzy If-Then rule assumes the form IF x is A then Y is B where A and B are linguistic values defined by fuzzy sets on the range X and Y, respectively [4].
3. Fuzzy inference engine: a process that elaborates and combines rule outputs.
4. Defuzzification: a process that transforms the fuzzy output into a crisp domain.

The most widespread methodologies for developing fuzzy rules systems are those proposed by Mamdani [19] and Takagi-Sugeno [20] methods. The two methods are similar in many aspects, the main difference is that the Takagi-Sugeno output membership functions are either linear or constants while the membership functions of Mamdani are linguistic. A typical rule in a Takagi-Sugeno model has the form [21].

IF input 1 = x and input 2 = y Then output is z = ax + by + c

The output level zi of each rule is weighted by the firing strength wi of the rule. For example for an AND rule with input 1= x and input 2= y the firing strength is

$$wi = \text{AndMethod}\ (F1(x), F2(y)) \qquad (1)$$

where F1,2(.) are the membership functions for inputs 1 and 2. The final output of the system is the weighted average of all rule output computed as

$$\text{Final output} = \frac{\sum_{i=1}^{N} w_i z_i}{\sum_{i=1}^{N} w_i} \qquad (2)$$

A Takagi-Sugeno rule operates as shown in Fig.3.

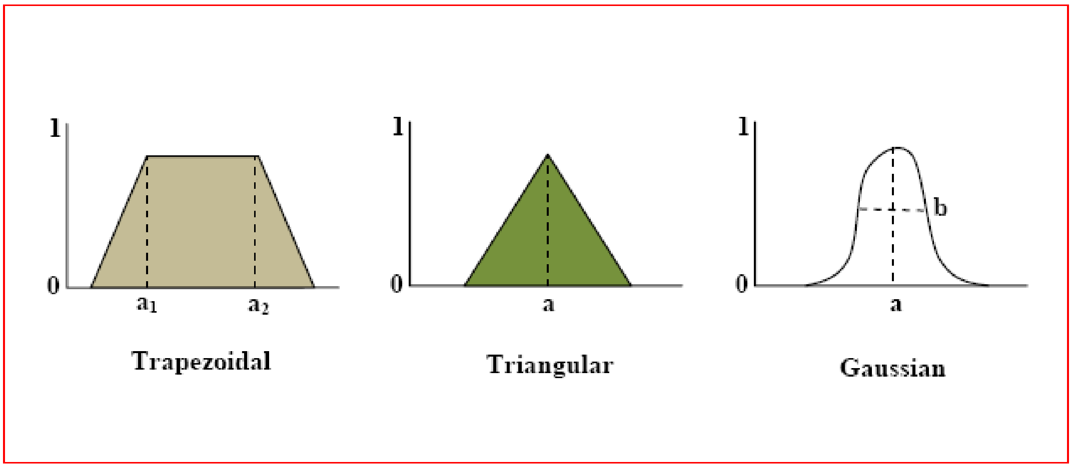

Fig. 1: The different shapes of membership functions

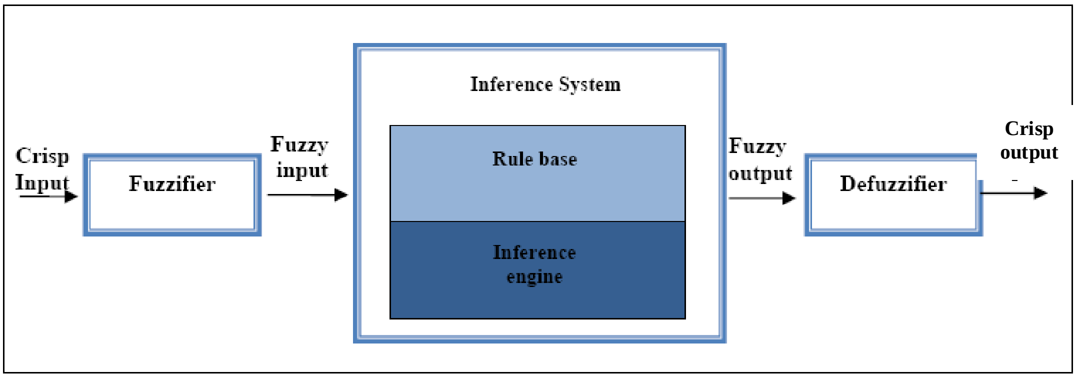

Fig. 2: Main components of fuzzy inference engine

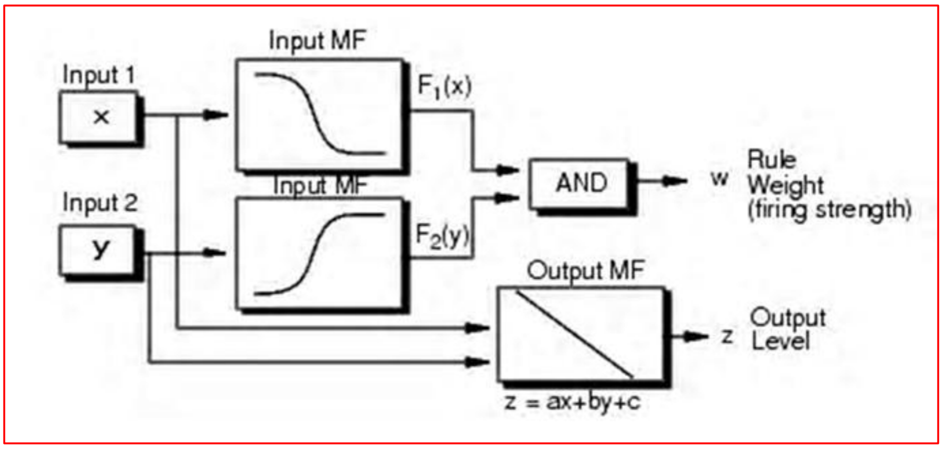

Fig. 3: Operation of Takagi-Sugeno fuzzy inference type (Matlab user guide, 2008)

Reservoir description

The Nasyria Oil Field is an anticline structure with northwest- southeast general trend. It is located in south of Iraq close to Nasyria city (Fig.4). Three reservoir units were discovered in this field: the Yamam, Nahr Umr, and Mishrif formations. The main reservoir of the field is Mishrif Formation that has a heterogeneous nature originally, described as organic detrital limestones, with beds of algal, rudist, and coral-reef limestones, capped by limonitic fresh water limestones [22]. The abundant fauna within the formation indicates that the formation is Cenomanian-Early Turonian age [23]. The average porosity and permeability of the formation is 22% and 23 md, respectively. The API gravity of oil is typically 23-36.6°[22].

Methodology

The data used in this study were collected from archive of South Oil Company of Iraq. A total of 206 core samples from three exploration wells (Ns-2, Ns-3, and Ns-5) were used to build a fuzzy model. Input data were divided into two groups including training set (170 data points) which represent the Ns-2 and Ns-3 wells; and testing set (36 data points which represent Ns-5). A plot of semi-log core permeability versus core porosity measurements from all the data is shown in Fig.5. The scatter of this data shows the high degree of heterogeneity in this reservoir.

A fuzzy toolbox in Matlab environment software was used to build a fuzzy model. A Takagi- Sugeno fuzzy inference engine was selected to generate permeability predictive model. Membership functions were extracted via subtractive clustering method. By specifying 0.45 for the calculus radius, three Gaussian membership functions were extracted for input variables (depth and log porosity) which were labeled as low, medium, and high for porosity and shallow, moderate, and deep for depth (Fig.6). A log scale was used for porosity and permeability because of a high range of both variables.

Three IF-THEN rules are generated. These are as follows

IF (depth is Deep) and (porosity is Low) THEN (permeability is Low)

IF (depth is Medium) and (porosity is Medium) THEN (permeability is Medium)

IF (depth is Shallow) and (porosity is High) THEN (permeability is High)

Results and Discussion

After extraction of membership functions and IF-THEN rules by subtractive clustering the Takagi-Sugeno model was constructed, Fig.(7). The data for testing well (Ns-5) were then entered through the fuzzy model and the results were compared with the measured core permeability, Fig.(8). A comparison of the whole measured and predicted permeability (training and testing data set) versus depth is shown in Fig.(9). Squared correlation coefficient (R2) is used to test the performance of the inference system. R2 the relative predictive power of a model is a descriptive measure between 0 and 1, which is defined as:

$$R^2 = 1 - \frac{SSE}{SSy} \qquad (3)$$

where

$$SSE = \sum_{i=1}^{n} \left(x_i - \hat{x} \right)^2 \qquad (4)$$

$$SSy = \sum_{i=1}^{n} \left(x_i - \bar{x} \right)^2 \qquad (5)$$

x = the measured values

$\hat{x}$ = the predicted values

$\bar{x}$ = The mean of the measured values

R2 values can be interpreted as indicators of how good are the results produced by the model. The close R2 is to one the better the model is. The high correlation coefficient of the test well (0.97) indicates the high performance of the fuzzy inference system to infer permeability from depth and porosity measurements. The fuzzy inference system built in this study for the Mishrif reservoir could be used to infer permeability for the new drilled wells without need to acquire cores. The predictive model uses only two variables to estimate permeability, depth and porosity, and these variables could be obtained from well logs data.

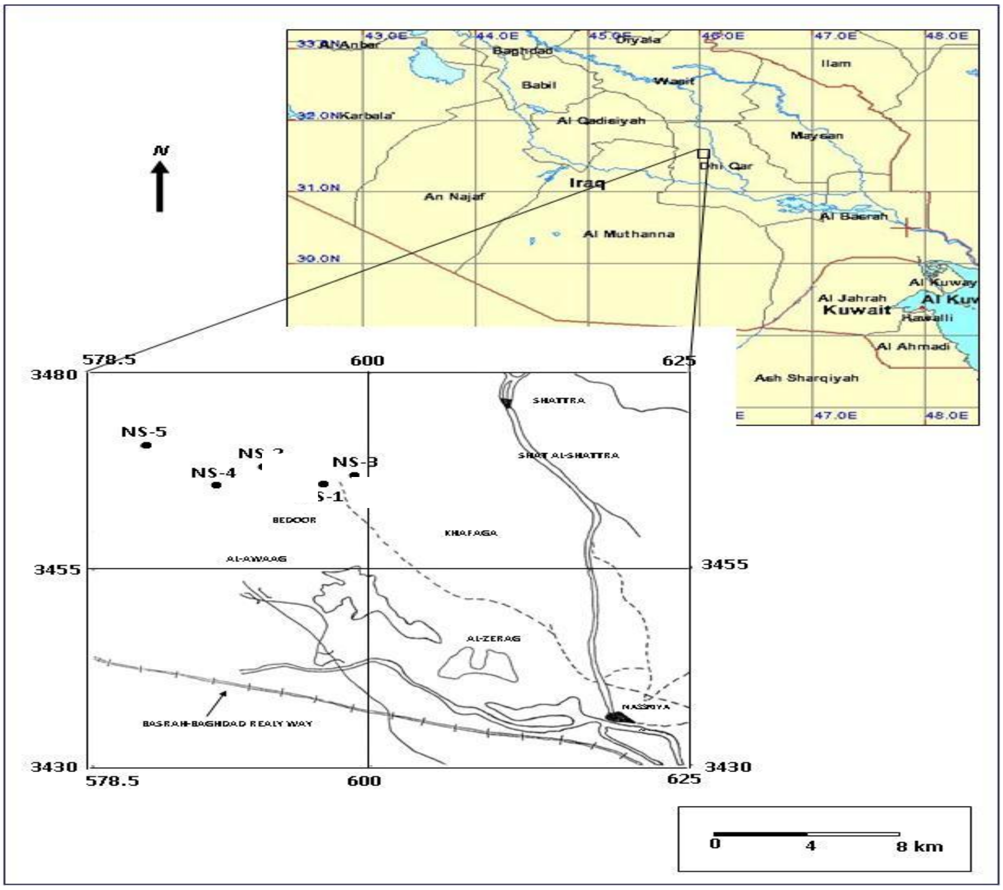

Fig. 4: Location map of the Nasyria oil field

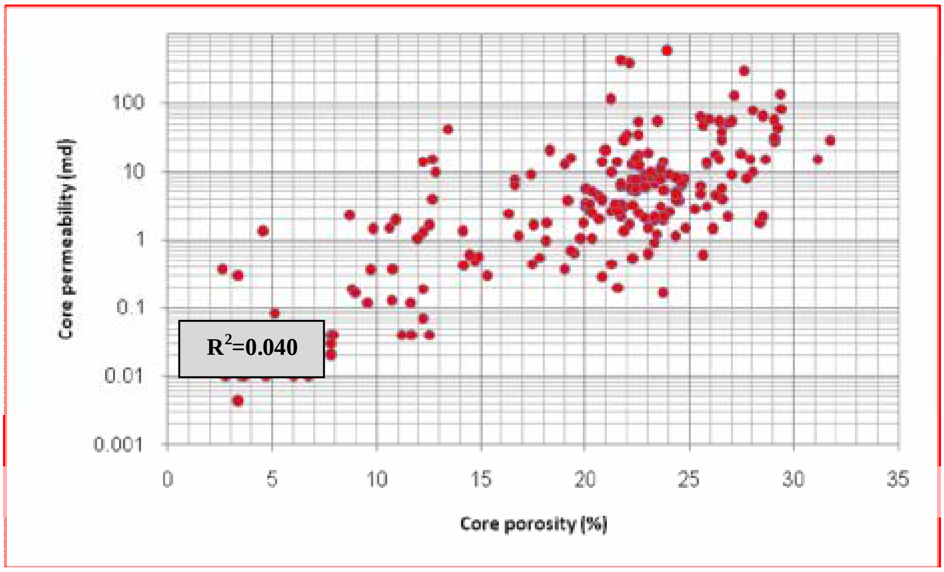

Fig.5: A scatter diagram of core porosity versus core permeability

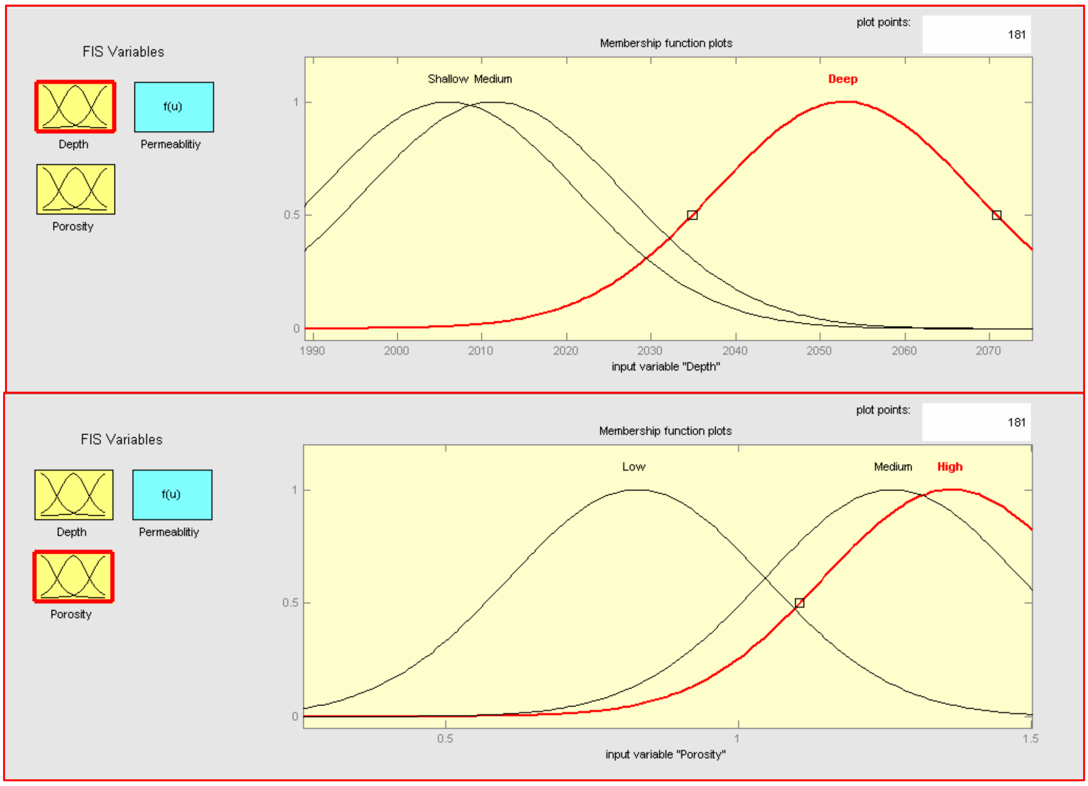

Fig.6: The membership functions for depth and porosity inputs

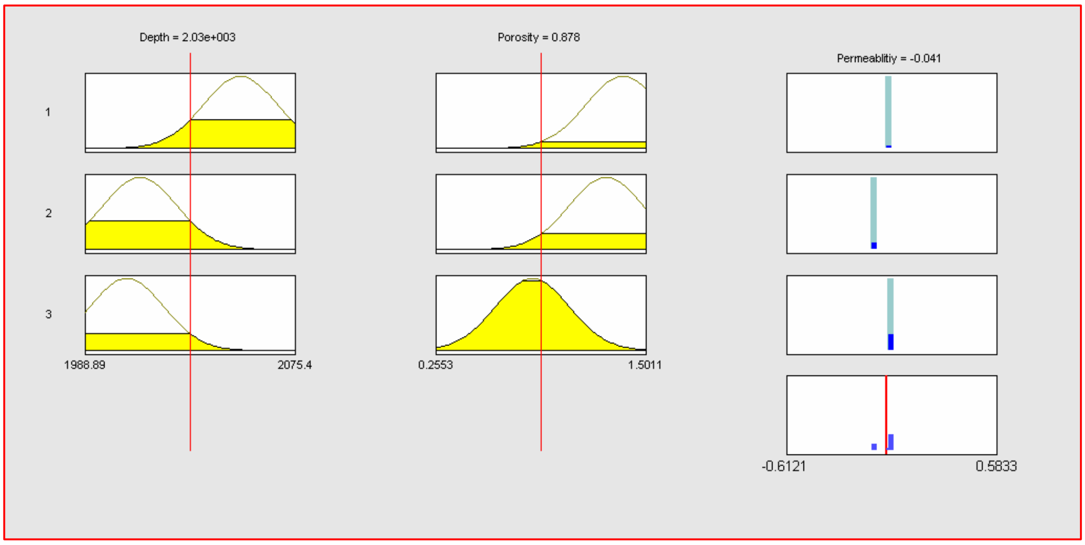

Fig.7: The used Takagi- Sugen inference system to infer permeability in this study

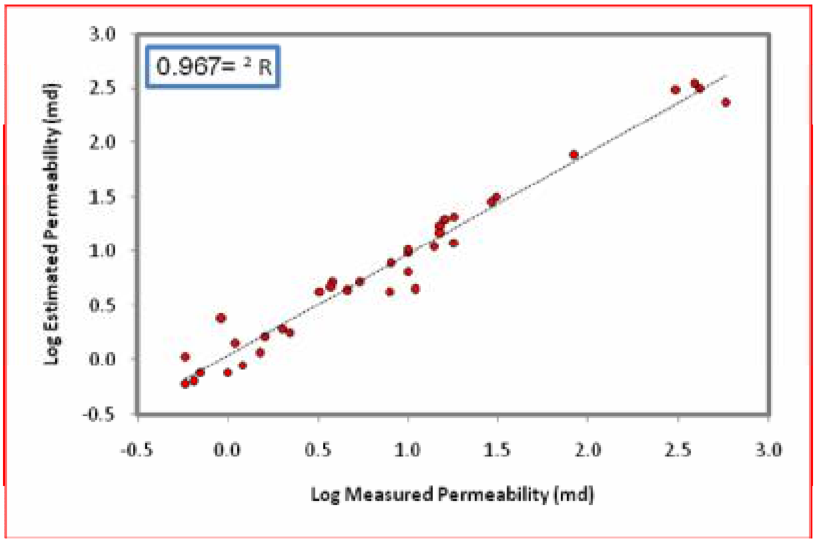

Fig.8: Crossplot showing correlation between measured and predicted permeability for the test well (Ns-5)

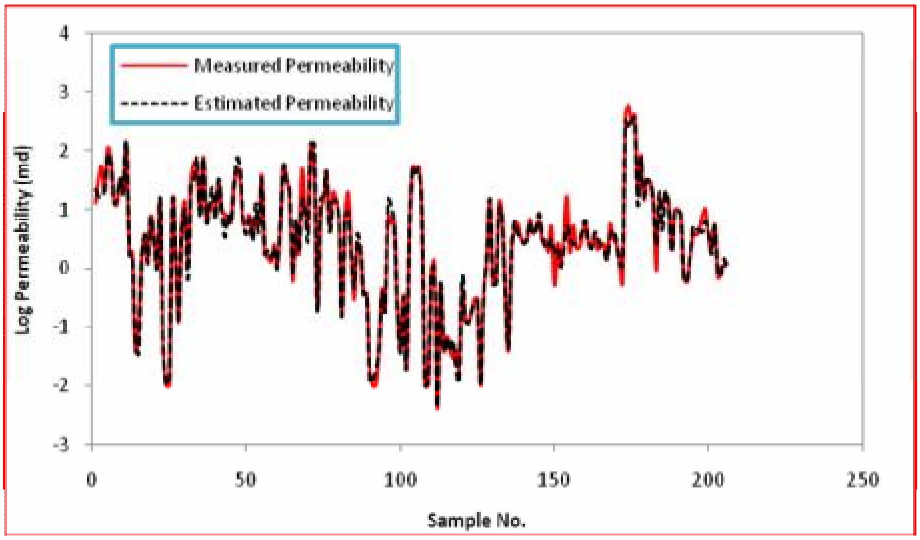

Fig.9: A comparison between measured and predicted using fuzzy system for training and testing data

Conclusions

Fuzzy inference system is a powerful technique to predict permeability from porosity and depth measurements. Only a few core permeability and porosity measurements are required first to build a fuzzy model and the fuzzy inference engine predicts permeability for other sites of the field by knowing depth and porosity inputs which can be taken from conventional well logs data. It is inexpensive and easy to construct models which overcome the need to coring process. We recommended using this technique in the oil industry of Iraq because of its high benefits.

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استخدام تقنية المنطق المضبب لتخمين قيمة النفاذية من قراءات المسامية والعمق لتكوين المشرف في حقل الناصرية ، جنوب العراق

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الخلاصة

تم في هذا البحث التحري عن امكانية تقنية الذكاء الصناعي المعروفة باسم المنطق المضبب لتخمين نفاذية تكوين المشرف في حقل الناصرية ، جنوب العراق باستخدام قراءات المسامية والعمق. يستخدم النموذج لوصف العلاقة اللاخطية بين العمق والمسامية كمدخلات له والنفاذية كمخرجات. استعمل 206 نموذج لباب جمعت من ثلاثة آبار استشكافية هي (Ns-2, Ns-3, Ns-5) لبناء النموذج المضبب. قسمت البيانات (قراءات المسامية والعمق والنفاذية) الى قسمين شمل القسم الاول 170 نقطة والتي تمثل البئرين (Ns-2, Ns-3) لتدريب النموذج (معايرته) و 36 نقطة التي تمثل البئر (Ns-5) لاختبار ادائية النموذج. تم اشتقاق دوال الانتماء وقواعد اذا-لو باستخدام تقنية الـ subtractive clustering . بينت النتائج امكانية النموذج المضبب لتخمين قيم النفاذية من قياسات العمق والمسامية فقط . استخدم معامل الارتباط لتقدير ادائية النموذج حيث بلغت القيمة المحسوبة لهذا المعامل 0.967 للمعلومات المستخدمة لاختبار الموديل المصمم. يحتاج النموذج في البداية لغرض بنائه ومعايرته الى قياسات النفاذية والمسامية والعمق للباب المأخوذ والمتوفرة في الحقل ثم يقوم النموذج المعاير بتخمين قيمة النفاذية للآبار التي لا يتوفر فيها لباب من قراءات المسامية والعمق والتي يمكن ان تحسب او توخذ من المجسات المختلفة.