

Permeability and Porosity Prediction from Wireline logs Using Neuro-Fuzzy Technique

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Abstract: Petroleum reservoir characterization is a process for quantitatively describing various reservoir properties in spatial variability using all the available field data. Porosity and permeability are the two fundamental reservoir properties which relate to the amount of fluid contained in a reservoir and its ability to flow. These properties have a significant impact on petroleum fields operations and reservoir management. In un-cored intervals and well of heterogeneous formation, porosity and permeability estimation from conventional well logs has a difficult and complex problem to solve by statistical methods. This paper suggests an intelligent technique using fuzzy logic and neural network to determine reservoir properties from well logs. Fuzzy curve analysis based on fuzzy logic is used for selecting the best related well logs with core porosity and permeability data. Neural network is used as a nonlinear regression method to develop transformation between the selected well logs and core measurements. The technique is demonstrated with an application to the well data in West July oil field, Gulf of Suez, Egypt for the Miocene Upper Rudeis reservoirs (Asal and Hawara formations). The results show that the technique can make more accurate and reliable reservoir properties estimation compared with conventional computing methods. This intelligent technique can be utilized as a powerful tool for reservoir properties estimation from well logs in oil and natural gas development projects.

INTRODUCTION

Reservoir characterization is a process of describing various reservoir characteristics using all the available data to provide reliable reservoir models for accurate reservoir performance prediction. The reservoir characteristics include permeability, porosity, pore and grain size distributions, facies distribution, and depositional environment. The types of data needed for describing the characteristics are core data, well logs, well tests, production data and seismic survey. Such information is essential to the determination of the economic viability of a particular well or reservoir to be explored. A large number of techniques have been introduced in order to establish an adequate interpretation model over the past fifty years. Nevertheless, conventional derivation of a well log data analysis model normally falls into one of the two main approaches: empirical and statistical. In the empirical approach, mathematical functions relating the desired permeability based on several well log data inspired by theoretical concepts are used [Wyllie and Rose, 1950, Kapadia and Menzie, 1985]. This approach has long been favored in the field and much effort has been made to understand the underlying petroleum engineering principles. However, the unique geophysical characteristic of each region prevents a single formula from being universally applicable.

Statistical techniques are viewed as more practical approaches [Wendt et al., 1986, and Hawkins, 1994]. The common statistical technique used is multiple regression analysis. The simplest form of regression analysis is to find a relationship between the input logs and the petrophysical properties. The derived

regression equations are then used for well log analysis. However, a number of initial assumptions of the model need to be made. Assumptions must also be made as to the statistical characteristics of the log data. Over the past decade, another technique that has emerged as an option for well log analysis is the Artificial Neural Network (ANN). Research has shown that an ANN can provide an alternative approach to well log analysis with improvement over the traditional methods [Osborne, 1992, Wong *et al.*, 1995, Fung and Wong, 1999]. Most of the ANN based well log analysis models have used the Multi-layer Neural Network (MLNN) utilizing the backpropagation learning algorithm. Such networks are commonly known as Backpropagation Neural Networks (BPNNs). A BPNN is suited to this application, as it resembles the characteristics of regression analysis in statistical approaches. Fuzzy Logic (FL) that is capable to express the underlying characteristics of a system in human understandable rules is also used. A fuzzy set allows for the degree of membership of an item in a set to be any real number between 0 and 1. This allows human observations, expressions and expertise to be modeled more closely. Once the fuzzy sets have been defined, it is possible to use them in constructing rules for fuzzy expert systems and in performing fuzzy inference. This approach seems to be suitable to well log analysis as it allows the incorporation of intelligent and human knowledge to deal with each individual case. However, the extraction of fuzzy rules from the data can be difficult for analysts with little experience. This could be a major drawback for use in well log analysis. If a fuzzy rule extraction technique is made available, then fuzzy systems can still be used for well log analysis [Wong *et al.*, 1999 and Kuo *et al.*, 1999]. With the emergence of intelligent techniques that combine ANN and fuzzy together have been applied successfully in well log analysis [Huang *et al.*, 2001, Kadkhodaie Ilkhchi *et al.*, 2008, Khaxar *et al.*, 2007, Johanyák *et al.* 2007]. These techniques used in building the well log analysis model normally address the disadvantages encountered in ANN and fuzzy system. This paper suggests an intelligent technique for reservoir characterization using fuzzy logic and neural network to determine reservoir properties from well log data for the Miocene Upper Rudeis reservoirs (Asal and Hawara formations), in West July oil field, Gulf of Suez, Egypt, Fig.1.

Back propagation neural networks (BPNN).

A neural network (NN) is an intelligent tool for solving complex problems. A BPNN is a supervised training technique that sends the input values forward through the network then computes the difference between calculated output and corresponding desired output from the training dataset. The error is then propagated backward through the net and the weights are adjusted during a number of iterations, named epochs. The training ceases when the calculated output values best approximate the desired values [Bhatt and Helle, 2002]. A flowchart of training procedure in a supervised NN is shown in Fig. 2.

Fuzzy logic (FL).

The basic theory of fuzzy sets was first introduced by Zadeh, 1965. In recent years, it has been shown that uncertainty may be due to fuzziness (possibility) rather than probability. FL is considered to be appropriate to deal with the nature of uncertainty in system and human errors, which were not considered in existing reliability theories. Generally, geological data are not clear-cut and habitually are associated with uncertainties. For example, prediction of core parameters from well log responses is difficult and is usually associated with error [Nikraves and Aminzadeh, 2003]. FL derives useful information from this error and applies it as a powerful parameter for increasing the accuracy of the predictions. A fuzzy inference system (FIS) is a method to formulate inputs to an output using FL [Kadkhodaie Ilkhchi *et al.*, 2006].

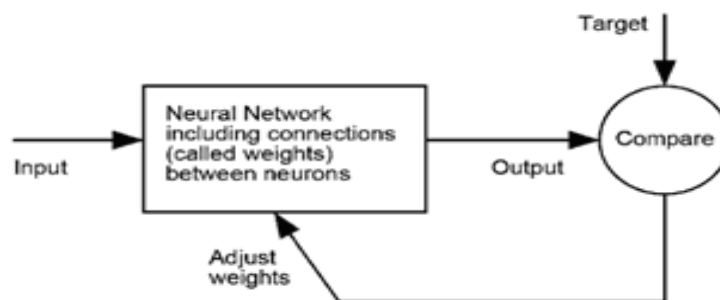
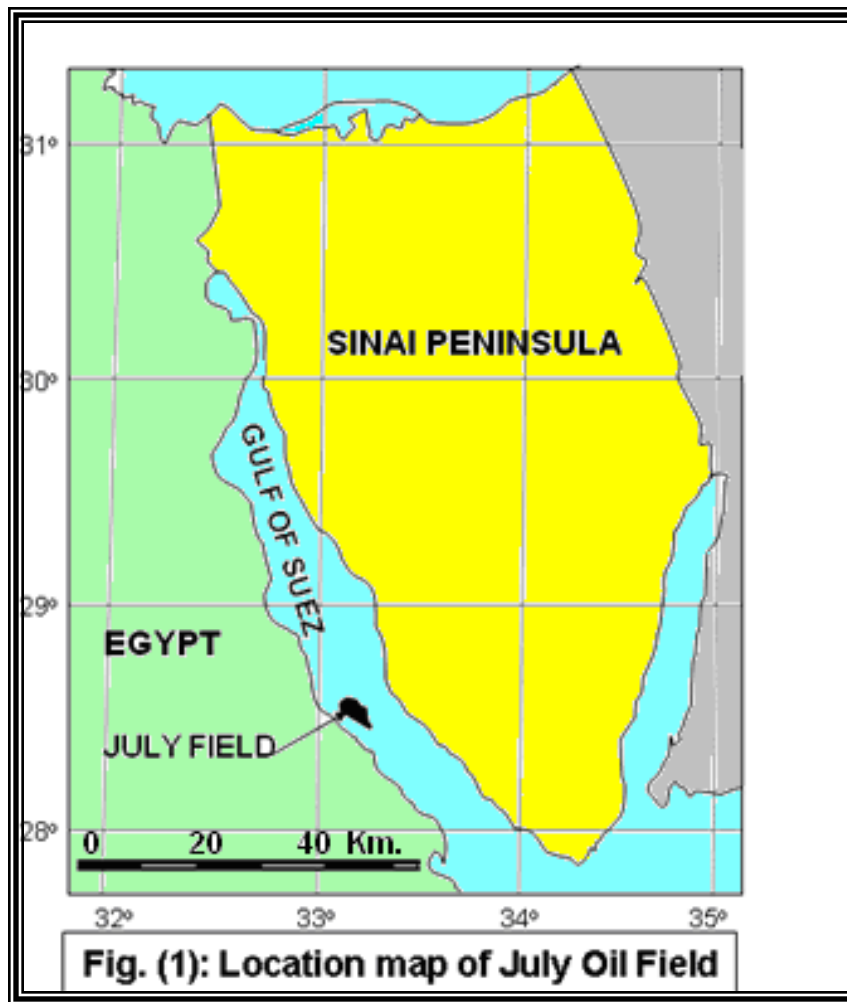


Fig.2. A flow chart of training procedure in a supervised neural network.

Fuzzy modeling technique can be classified into three categories, namely the linguistic (Mamdani-type), the relational equation, and the Takagi, Sugeno and Kang (TSK). Takagi and Sugeno, 1985, is a FIS in which output membership functions are constant or linear and are extracted by a clustering process. Each of these clusters refers to a membership function. Each membership function generates a set of fuzzy if-then rules for formulating inputs to outputs. A schematic diagram of FIS is shown in Fig.3.

Neuro-fuzzy (NF) model.

Hybrid NF systems combine the advantages of fuzzy systems (which deal with explicit knowledge) with those of NN (which deal with implicit knowledge). On the other hand, Fuzzy Logic (FL) enhances generalization capability of a Neural Network (NN) system by providing more reliable output when extrapolation is needed beyond the limits of the training data. A schematic diagram of information flows in a NF system is shown in Fig.4. The architecture of the Neuro-Fuzzy classifier is slightly different from the architecture used in function approximations [Tommi, 1994]. The two first layers have the identical function with the approximation. Fig. 5 shows a system using the following fuzzy rules,

Rule 1: If x_1 is A1 and x_2 is B1, then class is 1.

Rule 2: If x_1 is A2 and x_2 is B2, then class is 2.

Rule 3: If x_1 is A1 and x_2 is B3, then class is 1.

Layer 3. Combination of firing strengths: If several fuzzy rules have the same consequence class, this layer combines their firing strengths. Usually, the maximum connective (or operation) is used.

Layer 4. Fuzzy outputs: In this layer, the fuzzy values of the classes are available. The values describe how well the input of the system matches to the classes.

Layer 5. Defuzzification: If the crisp classification is needed, the best-matching class for the input is chosen as output class.

METHODS AND RESULTS

The data used for permeability and porosity determination are the open-hole wireline subsurface well log data [gamma ray (GR), sonic (DT), density (ROHB), deep resistivity (RD), Neutron (PHIN) logs, water saturation (SW)], and core data [core permeability and core porosity]. The work in the present research proceeds as following;

- Removing erroneous and outliers from the raw well log data.
- Organizing data into input data sets including GR, DT, ROHB, RD, PHIN, SW and output data sets including core permeability and core porosity.
- Normalization of input and output data sets (between the ranges 0-1) to renders the data dimensionless and removes the effect of scaling.
- Dividing the data into: training, checking and testing data sets.
- Clustering the input and output data sets using fuzzy c-means (FCM), fuzzy k-means (FKM) or subtractive clustering methods.
- Fuzzyfication, which involves the conversion of numeric data in real world domain to fuzzy numbers in fuzzy domain, this takes place by building the fuzzy inference system FIS, which involves setting the membership functions and establishment of fuzzy rules.
- Defuzzification, which is optional, involves the conversion of the derived fuzzy number to the numeric data in real world domain.

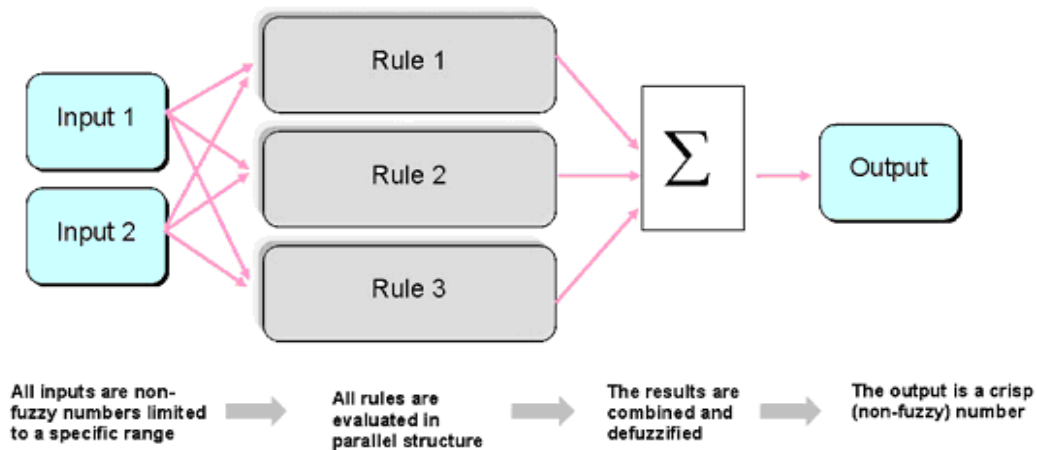


Fig.3. Schematic diagram of FIS

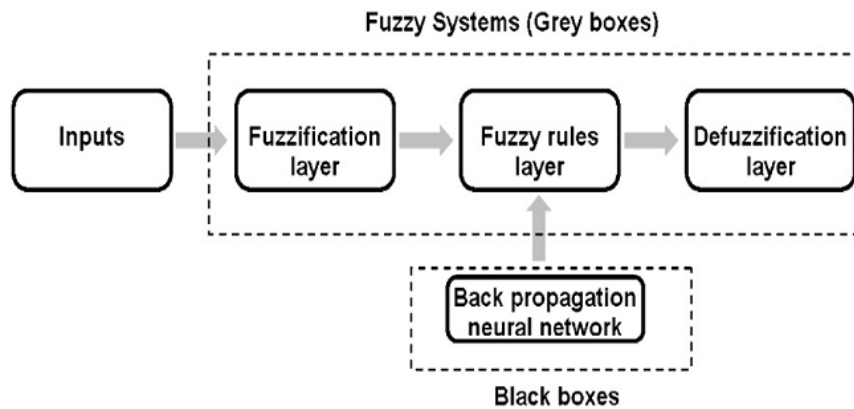


Fig.4. Schematic diagram of information flow in a NF system

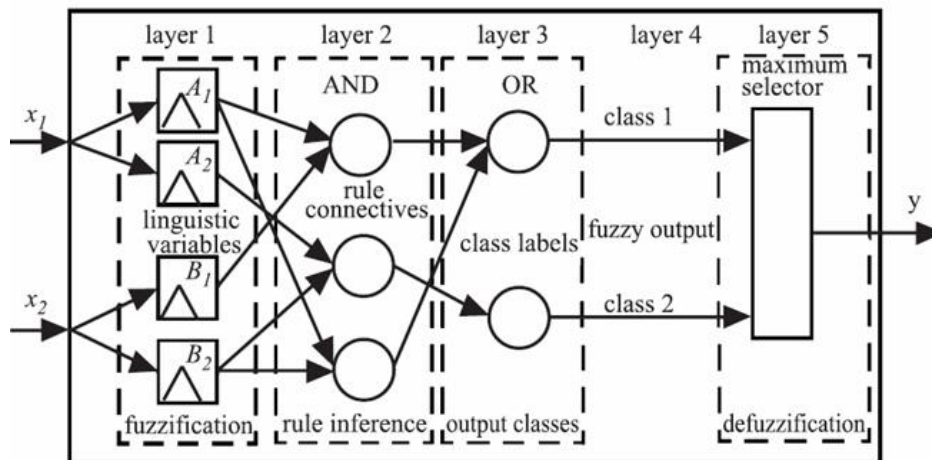


Fig.5. Neural architecture of the NF classifier.

•**Organizing data.** The data for the neuro-fuzzy model come from one well SG-3105A at West July oil field, Gulf of Suez, Egypt. The selection of this well is based on geological considerations; it contains reasonably good core coverage of the Upper Rudeis Formation. Core-log calibration was carefully carried out to compensate for differences in depth. Table (1), illustrates the statistics of the input and output data sets used in NF modeling.

Table (1). Statistics of input and output data sets.

Parameter	Minimum	Maximum	Mean	St. Deviation
Core K (md.)	1	262	32	51
Core PHI (v/v)	6	30	12	3
GR (API)	2	81	25	16
DT (us/ft.)	57	104	67	6
ROHB (gm/c)	1.88	2.66	2.47	0.09
RD (ohmm.)	0.88	45.23	8	10
PHIN (w/v)	0.05	0.56	0.1	0.05
SW (%)	12	100	74	25

•**Normalizing data.** When processing the actual materials, due to the different dimensions of the source rocks evaluation parameter, the volume level of actual data vary considerably. If we calculate by using the raw data directly, the indicating role of the data which has a larger volume would become more outstanding. While the indicator with a lower volume and a higher sensitivity will be underestimated. Thus, we should preprocess and normalize the raw data. In this work normalizing data takes place by using the maximum and minimum values of the data.

•**Fuzzy clustering.** It is necessary to classify the input and output datasets into groups using clustering methods. In this study, a subtractive clustering method, which is a useful and effective way to FL modeling, is used for extraction of clusters and fuzzy if-then rules. The details of subtractive clustering could be found in *Chiu [1994]*, *Chen and Wang [1999]*, *Jarrah and Halawani [2001]*. The important parameter in subtractive clustering which controls number of clusters and fuzzy if-then rules is clustering radius. This parameter could take values between the range of [0, 1]. Specifying a smaller cluster (say 0.1) radius will usually yield more and smaller clusters in the data resulting in more rules. In contrast, a large cluster radius (say 0.9) yields a few large clusters in the data resulting in few rules.

The effectiveness of a fuzzy model is related to the search for an optimal clustering radius, which is a controlling parameter for determining the number of fuzzy if-then rules. Few rules could not cover the entire domains, and more rules will complicate the system behavior and may lead to low performance of the model. Regarding the permeability model, four centers result from clustering, thus the fuzzy model was established by four fuzzy if-then rules and four membership functions for input and output data. Porosity model, on the other hand, contains five centers (clusters), five rules and five membership functions. Figures 6 and 7 shows the subtractive clusters of permeability and porosity data.

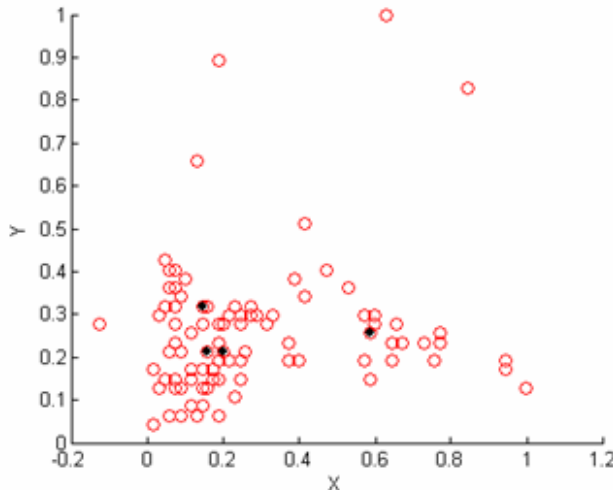


Fig. 6. Subtractive clustering of permeability fuzzy model.

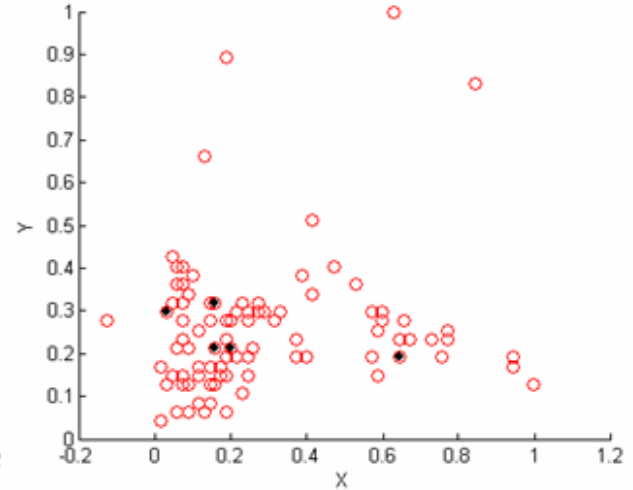


Fig. 7. Subtractive clustering of porosity fuzzy model.

• **Building the fuzzy inference system FIS.** 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 patterns discerned. The process of fuzzy inference involves setting the membership functions and establishment of fuzzy rules, [Matlab fuzzy logic user's guide, and 2009].

1- Setting the Membership Functions (MF). A membership function (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. The input space is sometimes referred to as the universe of discourse, a fancy name for a simple concept. The only condition a membership function must really satisfy is that it must vary between 0 and 1. The function itself can be an arbitrary curve whose shape we can define as a function that suits us from the point of view of simplicity, convenience, speed, and efficiency. There are many types of membership functions built from several basic functions:

- Piece-wise linear functions
- The Gaussian distribution function
- The sigmoid curve
- Quadratic and cubic polynomial curves

In this study, a Gaussian distribution membership function is used to define the extracted input clusters. A Gaussian function $f(x)$ shows the normal distribution of data (x):

$$f(X) = \frac{e^{-(x-\mu)^2/\sigma^2}}{\sigma\sqrt{2\pi}}$$

Where μ and σ are the parameters of normal distribution showing the mean and standard deviation of data, respectively. These Gaussian membership functions are constructed from mean and σ values of the clusters. The mean represents the cluster centers and σ is derived from:

$\sigma = (\text{radii} \times (\text{maximum data} - \text{minimum data}))/\text{sqrt}$. The input parameters of Gaussian membership function for permeability and porosity are shown in tables 2A and 3A.

Table (2): showing input (a) and output (b) membership functions parameters derived by FIS for permeability.

(A)

Inputs	GR(API)		DT(us/ft.)		ROHB(gm/cc.)		RD(ohm)		PHIN(v/v)		SW(%)	
Parameters	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ
Input MF no.												
MF1	0.2	0.16	0.17	0.21	0.17	0.77	0.18	0.05	0.17	0.10	0.17	0.91
MF2	0.2	0.59	0.17	0.25	0.17	0.70	0.18	0.01	0.17	0.10	0.17	0.98
MF3	0.2	0.14	0.17	0.32	0.17	0.65	0.18	0.03	0.17	0.21	0.17	0.53
MF4	0.2	0.20	0.17	0.21	0.17	0.73	0.18	0.37	0.17	0.11	0.17	0.20

(B)

Output	K (md.)						
	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Output MF no.							
MF1	-0.41	-0.60	-0.05	0.61	1.51	0.62	-0.47
MF2	-0.57	-0.19	-0.76	0.10	-0.18	-0.003	1.16
MF3	-0.15	0.11	0.15	-1.40	0.01	0.059	-0.05
MF4	0.31	0.22	-0.39	0.17	1.17	0.54	-0.05

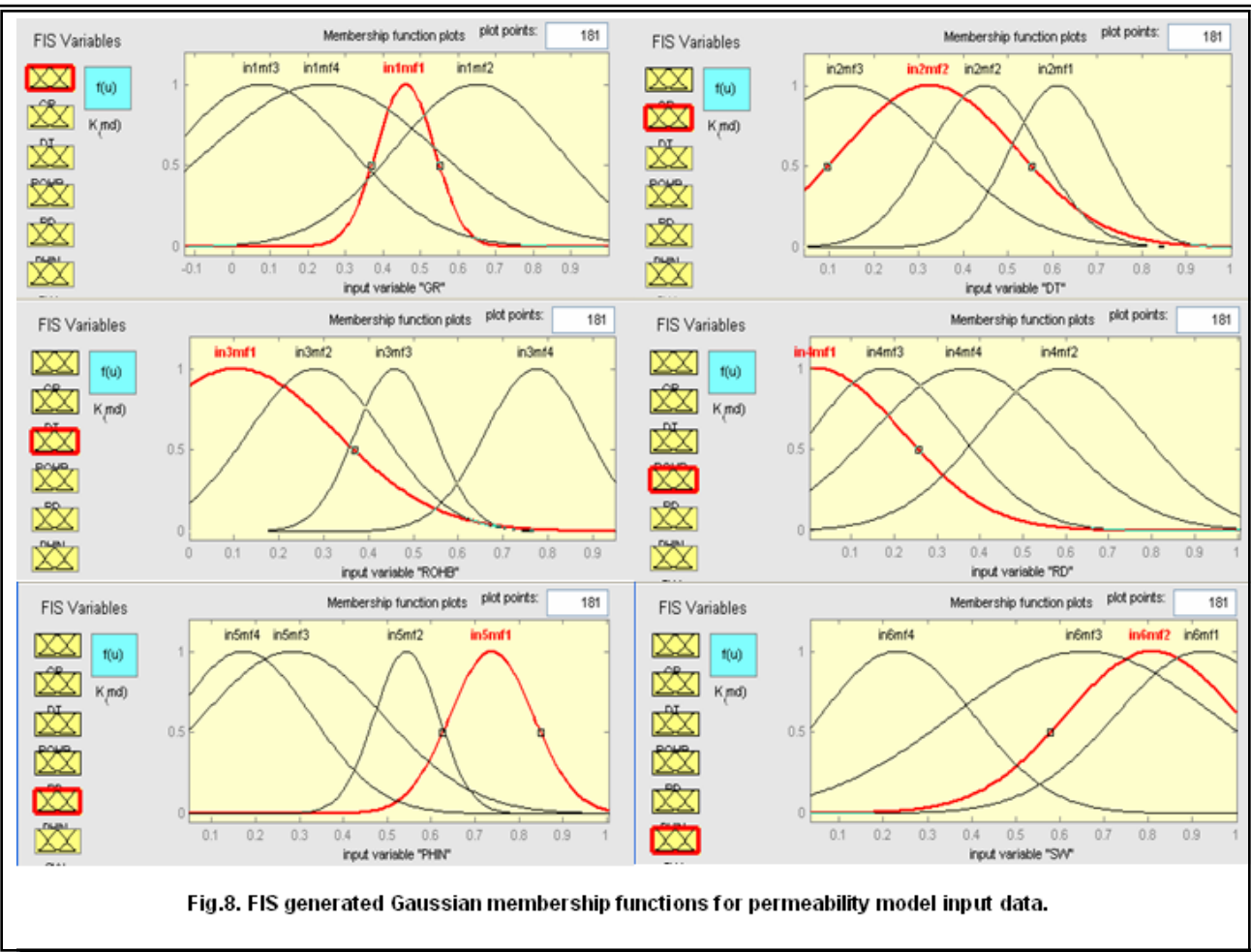
Table (3): showing input (a) and output (b) membership functions parameters derived by TS-FIS for porosity.

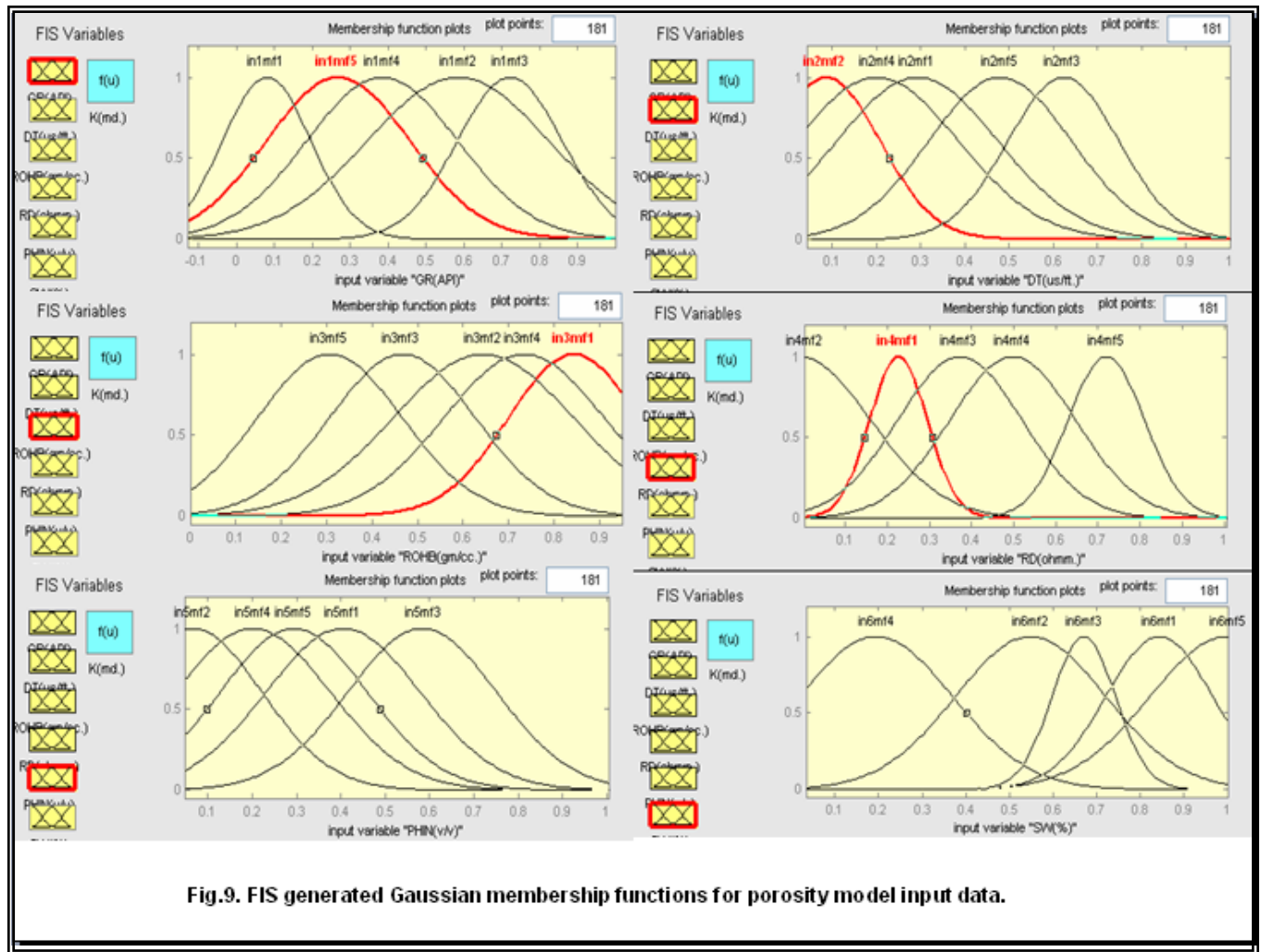
(A)												
Inputs	GR(API)		DT(us/ft.)		ROHB(gm/cc.)		RD(ohm)		PHIN(v/v)		SW(%)	
Parameters	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ
Input MF no.												
MF1	0.2	0.16	0.17	0.21	0.17	0.77	0.18	0.05	0.17	0.10	0.17	0.91
MF2	0.2	0.59	0.17	0.25	0.17	0.70	0.18	0.01	0.17	0.10	0.17	0.98
MF3	0.2	0.14	0.17	0.32	0.17	0.65	0.18	0.03	0.17	0.21	0.17	0.53
MF4	0.2	0.20	0.17	0.21	0.17	0.73	0.18	0.37	0.17	0.11	0.17	0.20
MF5	0.2	0.48	0.17	0.29	0.17	0.73	0.18	0.52	0.17	0.11	0.17	1.00
(B)												
Output	PHI(v/v)											
	C_1	C_2	C_3	C_4	C_5	C_6	C_7					
Output MF no.												
MF1	0	0	0	0	0	0	-0.17					
MF2	-0.36	0.29	-0.12	0.35	-0.57	-0.14	0.72					
MF3	0.31	-0.34	-3.30	15.81	3.87	2.57	-0.35					
MF4	0.18	0.39	-0.31	-0.14	0.14	-0.84	0.58					
MF5	0.74	0.82	-0.65	0.37	0.91	-0.41	0.61					

In the FIS, output membership functions are linear equations constructed from inputs. For example, output membership function number one (MF1), which is the consequent of rule no. 1, is constructed from six petrophysical inputs as following:

$$\text{Output MF1} = C_1 \times GR + C_2 \times DT + C_3 \times ROHB + C_4 \times RD + C_5 \times PHIN + C_6 \times SW + C_7$$

In this equation, parameters C_1, C_2, C_3, C_4, C_5 and C_6 are coefficients corresponding to GR, DT, ROHB, RD, PHIN and SW inputs, respectively. Parameter C_7 is constant in each equation. These parameters are obtained by linear least-squares estimation. With these explanations there will be seven parameters for each output membership function, which are shown in tables 2B and 3B for permeability and porosity, respectively. Figures 8 and 9 represent the FIS generated Gaussian membership functions of input data for permeability and porosity model, respectively.





Moreover, Figure 10 A shows the FIS model generated for permeability and porosity, (Fig.10B).

2- Establishment of fuzzy rules. Fuzzy 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 ranges (universes of discourse) X and Y , respectively. The if-part of the rule " x is A " is called the antecedent or premise, while the then-part of the rule " y is B " is called the consequent or conclusion.

The generated fuzzy if-then rules for formulating input petrophysical data to permeability are:

1. If (GR is in1mf1) and (DT is in2mf1) and (ROHB is in3mf1) and (RD is in4mf1) and (PHIN is in5mf1) and (SW is in6mf1) then (K is out1mf1).
2. If (GR is in1mf2) and (DT is in2mf2) and (ROHB is in3mf2) and (RD is in4mf2) and (PHIN is in5mf2) and (SW is in6mf2) then (K is out1mf2).
3. If (GR is in1mf3) and (DT is in2mf3) and (ROHB is in3mf3) and (RD is in4mf3) and (PHIN is in5mf3) and (SW is in6mf3) then (K is out1mf3).
4. If (GR is in1mf4) and (DT is in2mf4) and (ROHB is in3mf4) and (RD is in4mf4) and (PHIN is in5mf4) and (SW is in6mf4) then (K is out1mf4).

The generated fuzzy if-then rules for formulating input petrophysical data to porosity are:

1. If (GR is in1mf1) and (DT is in2mf1) and (ROHB is in3mf1) and (RD is in4mf1) and (PHIN is in5mf1) and (SW is in6mf1) then (PHI is out1mf1).
2. If (GR is in1mf2) and (DT is in2mf2) and (ROHB is in3mf2) and (RD is in4mf2) and (PHIN is in5mf2) and (SW is in6mf2) then (PHI is out1mf2).
3. If (GR is in1mf3) and (DT is in2mf3) and (ROHB is in3mf3) and (RD is in4mf3) and (PHIN is in5mf3) and (SW is in6mf3) then (PHI is out1mf3).
4. If (GR is in1mf4) and (DT is in2mf4) and (ROHB is in3mf4) and (RD is in4mf4) and (PHIN is in5mf4) and (SW is in6mf4) then (PHI is out1mf4).
5. If (GR is in1mf5) and (DT is in2mf5) and (ROHB is in3mf5) and (RD is in4mf5) and (PHIN is in5mf5) and (SW is in6mf5) then (PHI is out1mf5).

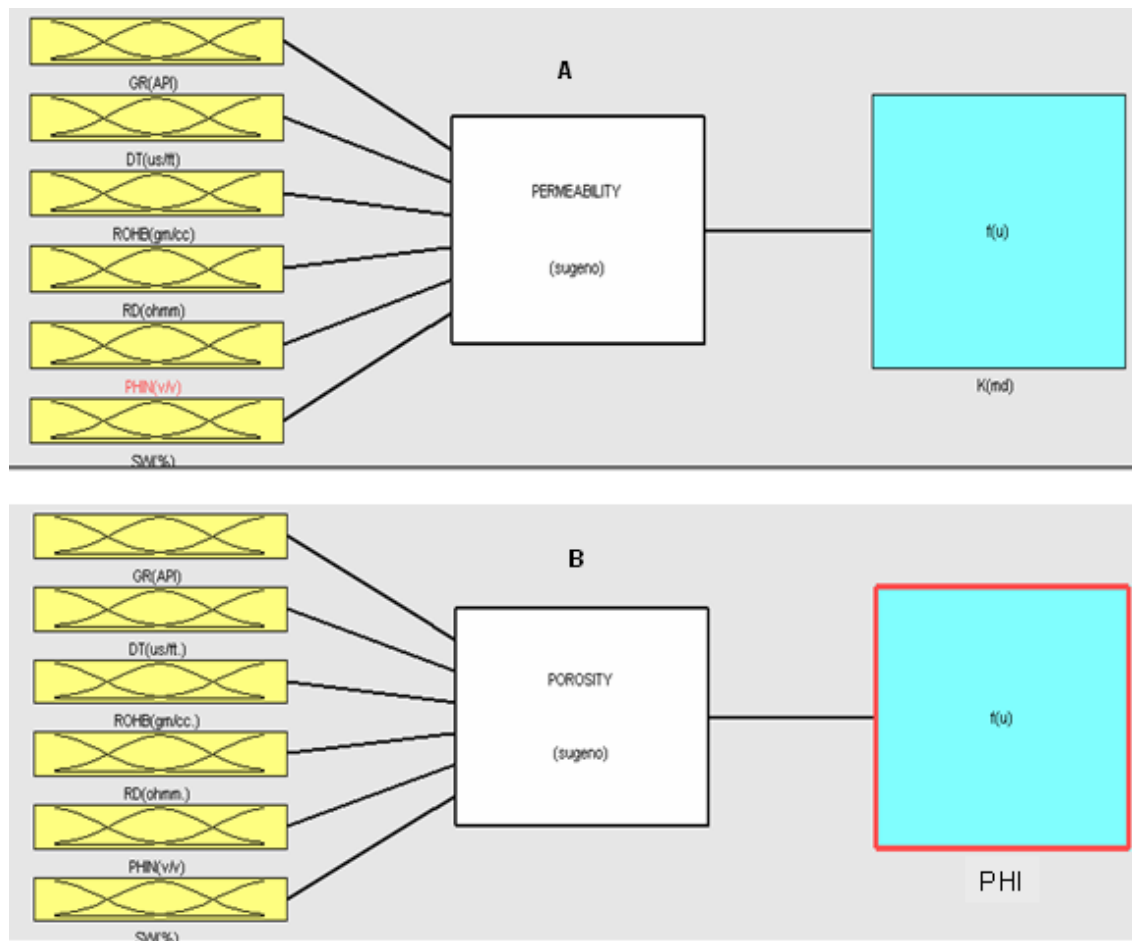


Fig.10. Diagrams showing formulation of input petrophysical data to: (A) permeability, K and (B) porosity, PHI using fuzzy modeling.

A graphical illustration showing steps to formulation of petrophysical data inputs to permeability using four fuzzy if-then rules generated by FIS, is represented in Fig.11. The formulation of petrophysical data to porosity using five fuzzy if-then rules generated by FIS are shown in Fig. 12. Each figure displays a roadmap of the whole fuzzy inference process. The seven plots across the top of the figure represent the antecedent and consequent of the first rule. Each rule is a row of plots, and each column is a variable. The rule numbers are displayed on the left of each row.

The structure of the NF model is now generated for permeability (Fig.13A) and porosity (Fig.13B). The input is represented by the left-most node and the output by the right-most node. The node represents a normalization factor for the rules.

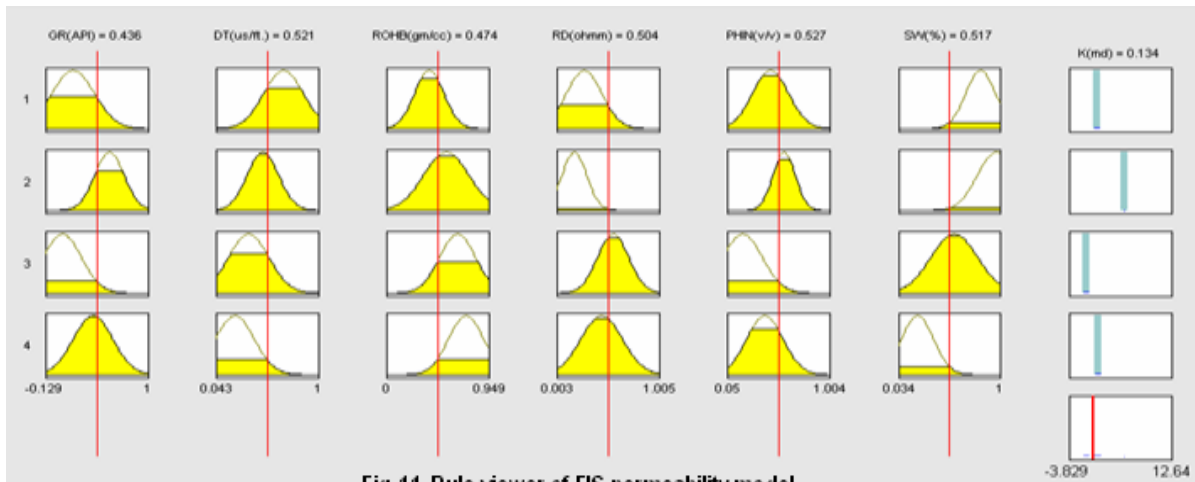


Fig.11. Rule viewer of FIS permeability model.

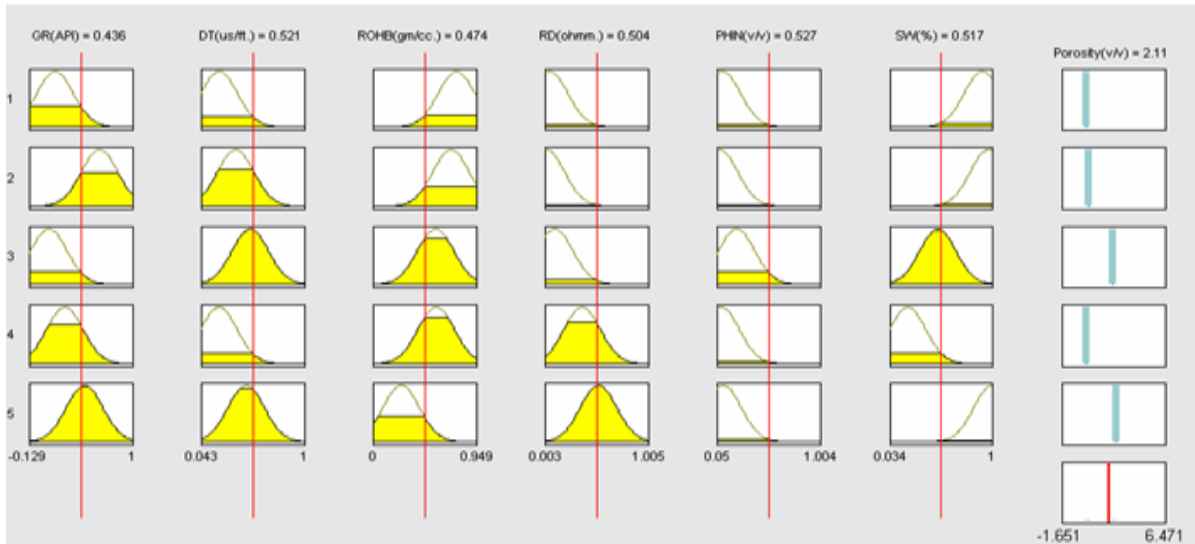


Fig.12. Rule viewer of FIS porosity model.

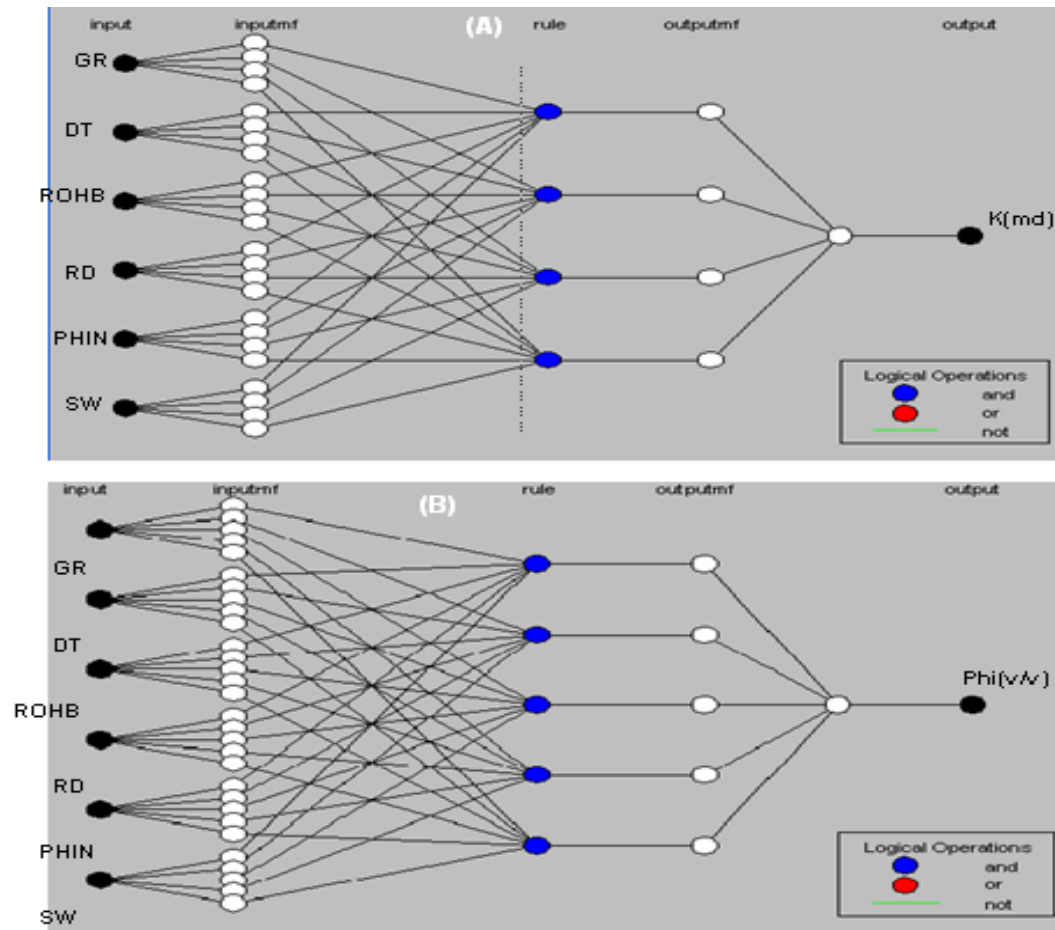


Fig.13. Structure of Neuro-Fuzzy Model for Permeability (A) and Porosity (B).

DISCUSSION

The NF technique is used to determine the porosity and permeability of the Upper Rudeis Formation using the available well data, as well as core permeability and core porosity data, (Fig. 14). The Upper Rudeis sand is the third most important reservoir in July oil field. The sand was supplied by fans draining the Red Sea hills to the west of July field and deposited in a similar environment to the Lower Rudeis Formation, *Pivnik et al., (2003)*.

A total of 108 data points are used for training, 108 data points are used for checking and 60 data points are used for testing the NF models of the permeability and porosity. The FIS is trained using the training data set then checked and tested using checking data sets and testing data sets respectively. The testing data set is used to check the generalization capability of the resulting fuzzy inference system. The idea behind using a checking data set for model validation is that after a certain point in the training, the model begins over fitting the training data set. In principle, the model error for the checking data set tends to decrease as the training takes place up to the point that over fitting begins, and then the model error for the checking data suddenly increases. Over fitting is accounted for by testing the FIS trained on the training data against the checking data. Usually, these training and checking data sets are collected based on observations of the target system and are then stored in separate files.

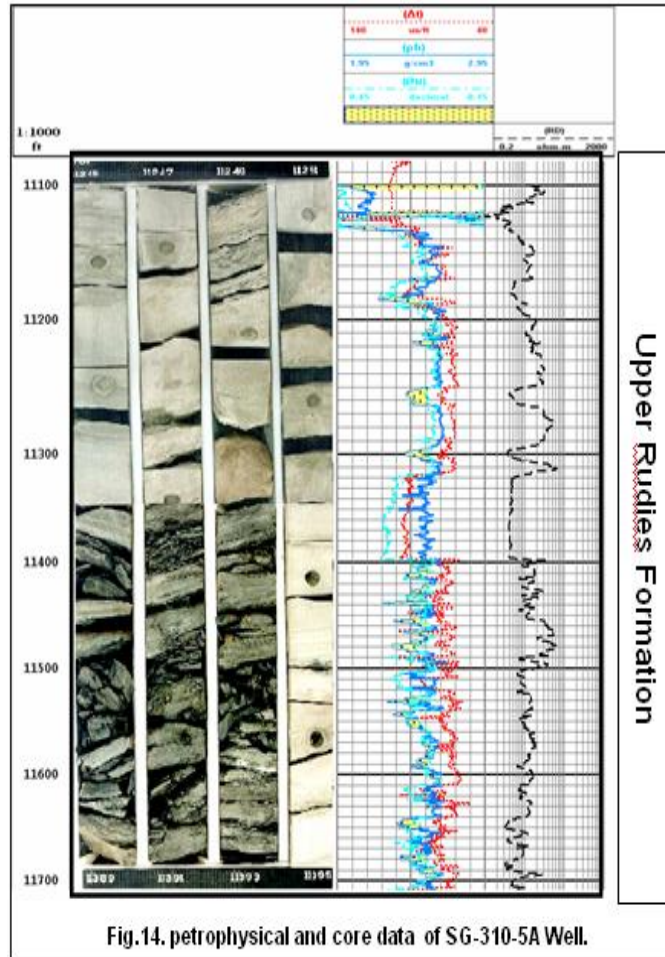


Figure 15 shows the checking and the FIS output. On the other hand, Fig.16. shows testing data and FIS output. The performance of the model is evaluated by the MSE of the data sets, as illustrated in Fig.17. and table (4). The correlation coefficient between the measured and NF predicted K and PHI are 0.825 and 0.957, respectively. A comparison between measured and NF predicted K and PHI versus depth is shown in Figs. 18 and 19.

Table (4). MSE of the different datasets.

Mean Square Error (MSE)		
Data Set	Permeability	Porosity
Training	0.10542	0.0508
Checking	0.1973	0.0582
Testing	0.31866	0.1518

CONCLUSIONS

In this study, the NF intelligent technique is used to estimate reservoir porosity and permeability from conventional well logs. Fuzzy curve analysis based on fuzzy logic can be used for selecting the best related parameters with reservoir properties. The NF modeling approach presented in this paper has been successfully applied for the prediction of petrophysical reservoir parameters. This modeling approach has the significant advantage in that it does not require any previous assumption based on physical or experimental considerations about the reservoir complexities to construct a reasonable and accurate model from a set of measured data. Excellent correlation coefficients have been obtained for porosity 0.957, and permeability 0.825, using NF models. The techniques can make more accurate and reliable reservoir properties estimation and can be utilized a powerful tool for reservoir properties determination from well logs in petroleum industry, and is applicable in different wells and oil fields.

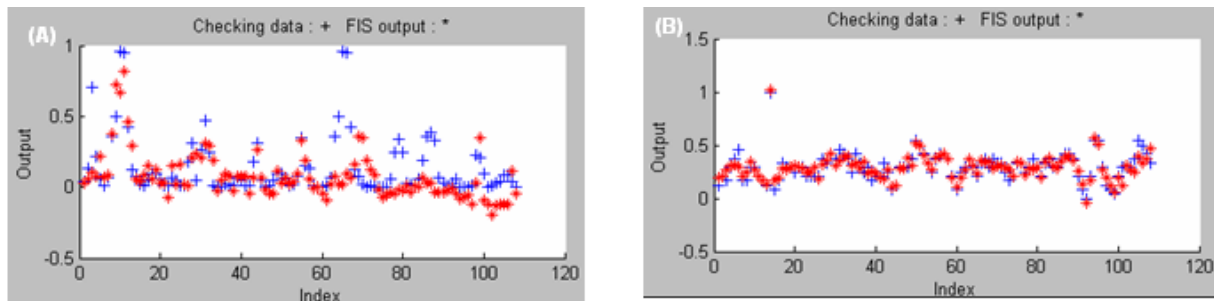


Fig.15. Showing checking data and FIS output, [permeability (A) and porosity (B)].

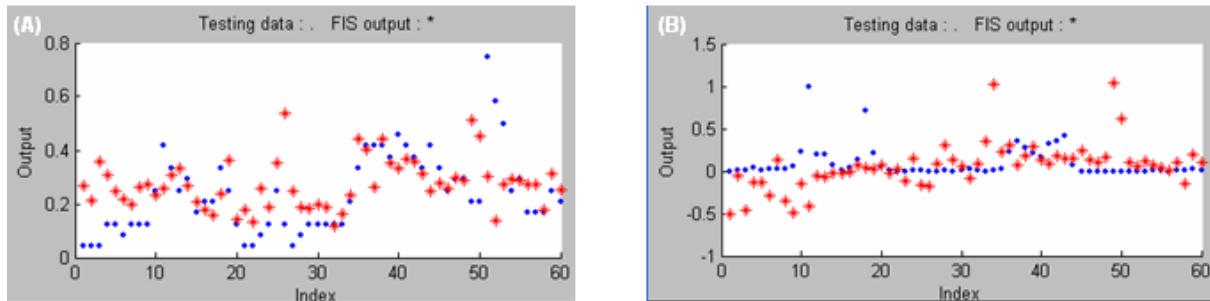


Fig.16. Showing testing data and FIS output, [permeability (A) and porosity (B)].

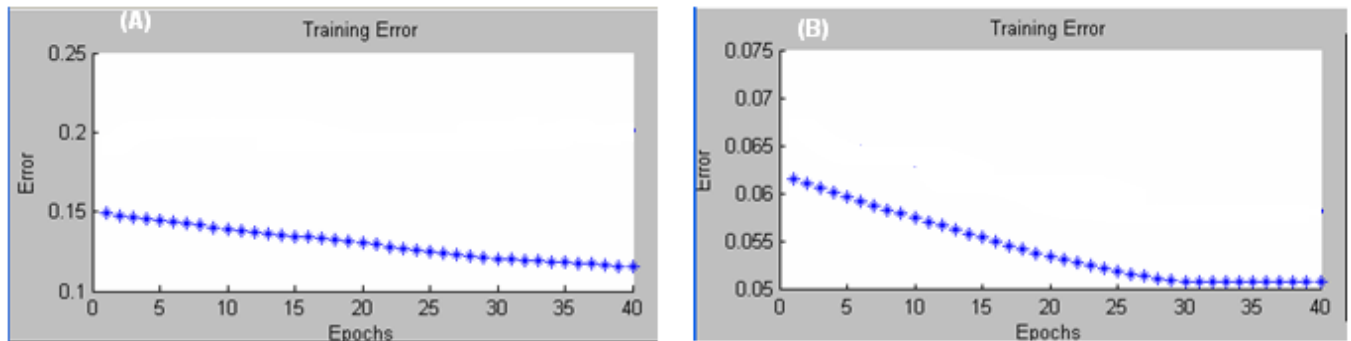


Fig.17. Mean Square Error (MSE) obtained during training the permeability model (A) and the porosity model (B).

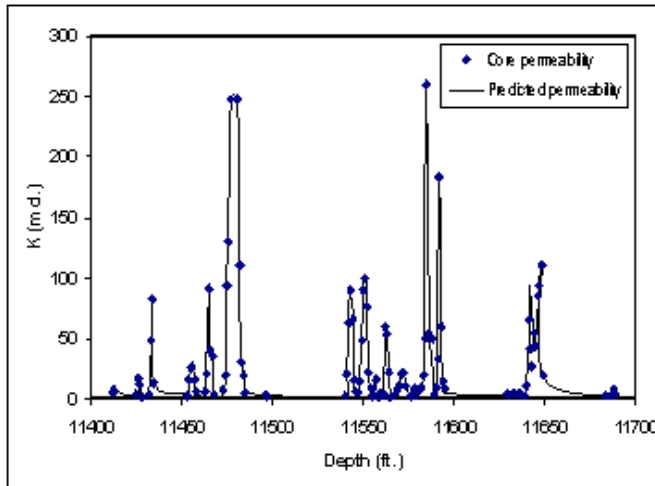


Fig.(18). Predicted and core permeability

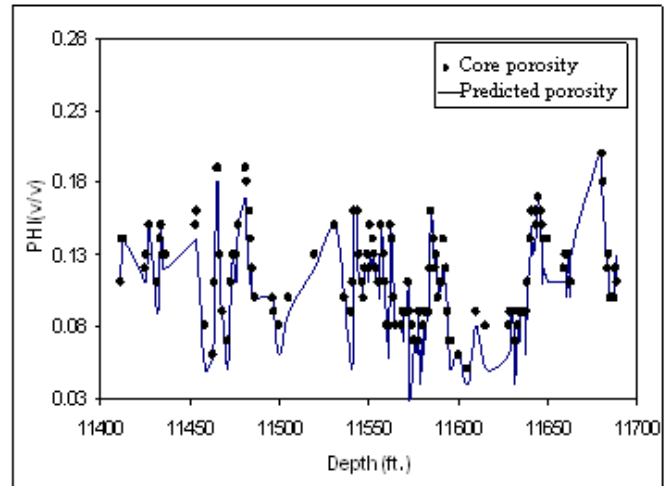


Fig.(19). Predicted and core porosity

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