A committee machine approach for predicting permeability from well log data: a case study from a heterogeneous carbonate reservoir, Balal oil Field, Persian Gulf

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Abstract
Permeability prediction problem has been examined using several methods such as empirical formulas, regression analysis and intelligent systems especially neural networks and fuzzy logic. This study proposes an improved and novel model for predicting permeability from conventional well log data. The methodology is integration of empirical formulas, multiple regression and neuro-fuzzy in a committee machine. A committee machine, a new type of neural network, has a parallel structure in which each of the applied methods (experts) has a weight coefficient showing its contribution in overall prediction. The optimal combination of the weights is obtained by a genetic algorithm. The method is illustrated using a case study from a heterogeneous Upper Jurassic carbonate reservoir in Balal oil Field, Persian Gulf. For this purpose, one hundred fifty-one samples from the intervals comprising core and well log data were clustered into eighty-one training sets and seventy testing sets to evaluate the validity of the models developed. The results of this study show that the genetic algorithm optimized committee machine has provided more accurate results than each of individual experts used.
Keywords: *Permeability, Empirical formulas, Multiple regression analysis, Neuro-fuzzy, Committee machine, Balal oil field, Persian Gulf*

Introduction

Accurate estimation of the permeability is one of the important challenges in reservoir characterization studies. So far, numerous researchers such as Wong *et al*., (1997), Cuddy (1998), Arpat *et al*., (1998), Ali and Chawathe (1999), Chang *et al*., (2000), Huang *et al*., (2001), Bhatt and Helle (2002), Mohammad Pour *et al*., (2004), Lim (2003, 2005), Kadkhodaie *et al*., (2005), and Kadkhodaie *et al*., (2006) have tried out to make a quantitative formulation between well log responses and core derived permeability using several methods such as neural network, fuzzy logic, multiple regression and empirical formulas. Combining the results obtained from several techniques to solve a problem may improve the final solution. A committee machine (CM) has a parallel structure that produces a final output by combining the results of individual experts using an optimization technique (Haykin, 1991, Sharkey, 1996). The experts may be neural networks, empirical formulas or other algorithms (Chen & Lin, 2006). Genetic algorithms (GA) are one of the effective optimization techniques for constructing CM which are based on the principles of natural selection and genetics (Holland, 1975). They are often described in biological terms. Potential solutions are called chromosomes. A set of chromosomes is called a population and a problem to be solved can be represented by a fitness function. Genetic operators such as crossover and mutation are used to create a new population (Reformat, 1997). More details about GAs can be found in Goldberg (1989), Lucasius and Kateman (1993, 1994), Whitley and Vose (1995), and Huang *et al*., (2001).

This study integrates best empirical formula, best multiple regression formula and best intelligent model (neuro-fuzzy) in a committee machine to develop an improved model for predicting permeability in Balal oil Field, Persian Gulf (Figure 1).

Material and Methods

Methodology: Committee machine

The proposed methodology consists of four steps: (1) selection of best empirical formula; (2) construction of multiple regression formula; (3) construction of neuro-fuzzy model; and (4) construction of CM. The methodology was used in this study is an improved and novel model for predicting permeability from two points of view: 1. using CM concept for combining different models and thus using all of the work that have been done so far, and 2. using genetic algorithms for determining the contributions (weights) of individual experts used in constructing CM. It is clear that many components of the method described in this study are based on other works which are not novel in their own right (i.e. empirical formulas, neuro-fuzzy or genetic algorithms). Overall, the integrated technique described in this research can be considered as an efficient and more accurate way for predicting permeability from conventional well log data.

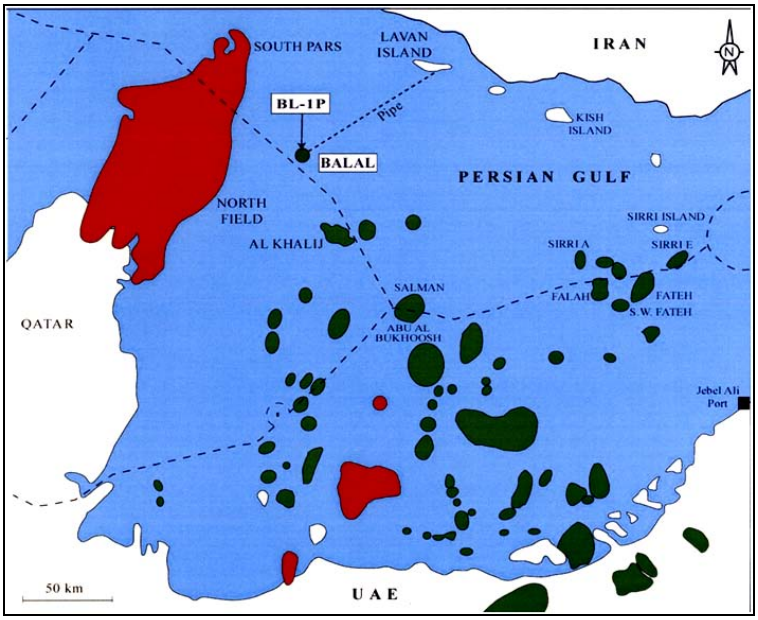

Figure 1: Location map of Balal oil Field in the Persian Gulf (Guly, 2000)

Selection of best empirical formula

Theoretical models offer an insight into physical processes that are controlling permeability (Kwon & Pickett, 1975). They are based on statistical relationships between permeability and parameters such as pore-throat radius, grain size and sorting, specific surface area, irreducible water saturation, and cation exchange capacity. In this study, empirical formulas including Cateso formula (Eq. (1)) (Owolabi *et al*., 1994), Wyllie–Rose formula (Eq. (2)) (Wyllie & Rose, 1950), Coates–Dumanior formula (Eq. (3)) (Coates and Dumanoir, 1973), and porosity formula (Eq. (4)) (Schlumberger Limited, 1991) were used to predict permeability.

$$k = M \times \phi^{D}((1-S_{Wirr})/(S_{Wirr}))^{F} \qquad (1)$$

$$k = PC \times (\phi^{PE})/(S_{wirr}^{SE}) \qquad (2)$$

$$k^{1/2} = (C/L^{4}) \times (\phi^{2L}/(R_{w}/R_{tirr})) \qquad (3)$$

$$k = 10^{(M\times\phi+KC)} \qquad (4)$$

where

$S_{wirr} = PS/\phi$,

$$L^{2} = (3.75-\phi)+((\log(R_{w}/R_{tirr})+2.2)^{2}/2)$$

k: Permeability, md

ϕ: Porosity fraction

S_{wirr}: Irreducible water saturation, fraction

R_w: Formation water resistivity, Ohm-m

R_{tirr}: Formation resistivity at irreducible water saturation, Ohm-m

M: Porosity exponent in Eq. (1)

D: Porosity exponent in Eq. (1)

F: Constant in Eq. (1)

PC: Permeability constant in Eq. (2)

PE: Porosity exponent in Eq. (2)
SE: Exponent of S_{wirr} in Eq. (2)
C: Constant in Eq. (3)
L: Constant in Eq. (3)
M: Constant in Eq. (4),
KC: Porosity coefficient in Eq. (4)
PS: Constant

To construct empirical formulas for the studied reservoir, coefficients *M, D, F* in Eq. (1), *PC, PE, SE* in Eq. (2), *C* in Eq. (3), and *M, KC* in Eq. (4) were determined using GA. After determination of the coefficients, permeability was calculated using the equations 1 through 4 and the best formula with the lowest root mean squared error (RMSE) was selected as one of the experts for constructing CM.

Construction of multiple regression formula

Multiple regression analysis (MRA) is an alternative approach used in the studied reservoir for permeability estimation. MRA has been widely used to model the relationship between inputs and outputs and can be generally expressed as below.

$$Y = f(X_1,...,X_n;\theta_1,...,\theta p) + \varepsilon, \qquad (5)$$

Where Y is a dependent variable (i.e., output variable), $X_1,...,X_n$ are independent or explanatory variables (i.e. input variables), $\theta_1,...,\theta p$ are regression parameters, ε is a random error, assumed to be normally distributed with zero mean and constant, and f is a known function, which may be linear or nonlinear.

If f is linear, then becomes a multiple linear regression model and can be expressed as $Y = b_0 + b_1X_1 + b_2X_2 + ... + b_nX_n + \varepsilon$, where b_0 is a constant (intercept). The regression parameters $\theta_1,...,\theta p$ are usually estimated using the least squares method, which can be expressed as an unconstrained optimization problem:

Minimize $J = \sum_{t=1}^{T}(Y_t - f(X_{1t},...,X_{nt};\theta_1,...,\theta p))^2$ (6)

Where *t =1,…, T* represents *T* different sample points. Once the regression parameters are determined, the corresponding regression model can be utilized for prediction.

An important advantage of MRA is that the regression parameters are easily interpreted so that the parameters, which make no sense, can be deleted from the model or be imposed on some constraints.

Construction of neuro-fuzzy (NF) model

NF hybrid systems combine the advantages of fuzzy systems (grey boxes) which deal with explicit knowledge and neural networks (black boxes) which deal with implicit knowledge. On the other hand, fuzzy logic enhances the generalization capability of a neural network system by providing more reliable output when extrapolation is needed beyond the limits of the training data. A schematic diagram of information flow chart in a NF system is shown in Figure 2. This method was used to formulate input well log data to permeability. In NF model, Gaussian membership functions and their parameters were extracted by a back-propagation neural network and fuzzy rules were derived by a fuzzy inference system (Nikravesh & Aminzadeh, 2003).

Construction of CM

Generally, a committee machine (Figure 3) consists of a group of experts which combines the outputs of each system and thus using all of the work, with little additional computation. So, performance of the model can be better than best single network (Haykin, 1991; Sharkey, 1996; Chen & Lin, 2006). There are different ways of combining the experts in the combiner. The simple ensemble averaging method is most popular (Naftaly *et al.*, 1997, Chen & Lin, 2006). Proper combination of contribution (weight) of individual experts in a committee machine can be obtained by a genetic algorithm.

The section below describes the fundamental of the CM constructed in this study with regard to the works of Bates and Granger (1969), Haykin (1991), Geman *et al*., (1992), Naftaly *et al*. (1997), Huang *et al*., (2001), Ligtenberg and Wansink (2001), Bhatt and Helle (2002), Lim

(2005), and Chen & Lin (2006).

Assuming that there are N expert systems with output vector of o_i that can be used to predict target vector T. The prediction error can be written as

$$e_i = o_i - T\,, \qquad (7)$$

The sum of the squared error for the i^{th} export o_i is

$$E_i = \xi[(o_i - T)^2] = \xi[e_i^{\,2}], \qquad (8)$$

In which $\xi[.]$ is the expectation. The average error for each algorithms acting alone is

$$E_{avg} = \frac{1}{N}\sum_{i=1}^{N} E_i = \frac{1}{N}\sum_{i=1}^{N} \xi[e_i^{\,2}], \qquad (9)$$

Applying the averaging method, output vector o_i of the CM is:

$$O_{CM} = \frac{1}{N}\sum_{i=1}^{N} o_i\,, \qquad (10)$$

Therefore, the CM has the prediction squared error:

$$E_{CM} = \xi[(O_{CM} - T)^2] = \xi[(\frac{1}{N}\sum_{i=1}^{N} o_i - T)^2] = \xi[(\frac{1}{N}\sum_{i=1}^{N} e_i)^2], \qquad (11)$$

Considering Cauchy's inequality:

$$(a_1b_1 + a_2b_2 + ... + a_nb_n) \le (a_1^2 + a_2^2 + ... + a_n^2)(b_1^2 + b_2^2 + ... + b_n^2,) \qquad (12)$$

$$E_{CM} = \xi[(\frac{1}{N}\sum_{i=1}^{N} e_i)^2] \le \frac{1}{N}\sum_{i=1}^{N} \xi[e_i^{\,2}] = E_{avg} \qquad (13)$$

Which indicates the CM gives more accurate and reliable estimations than any one of the individual algorithms.

In this research, the CM was used for overall prediction of permeability by combining the results obtained from empirical formula, MRA and NF (Figure 4). Actually, CM methodology involves two steps. The first step is estimation of permeability using MRA, NF and empirical formulas. In the second step their results are averaged depending on their contribution (weight) in the accuracy of estimations. The more weights will be assigned to the more accurate methods and vice versa such that all weights must add up to 1. The following equation is used for final prediction of permeability by CM:

$$k_{CM} = w_1 \times k_{\text{from empirical formula}} + w_2 \times k_{\text{from MRA}} + w_3 \times k_{\text{from NF}} \qquad (14)$$

Where w_1, w_2 and w_3 are the weight factors corresponding to the predictions of empirical formulas, MRA, and NF, respectively. The optimal combination of the weights is obtained by applying a GA for training data.

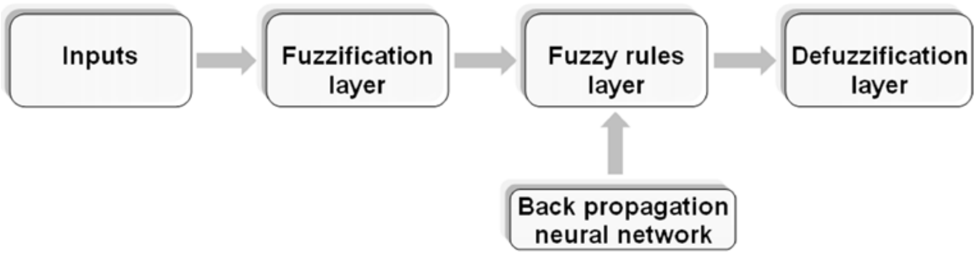

Figure 2: A schematic diagram of information flow chart in a NF system.

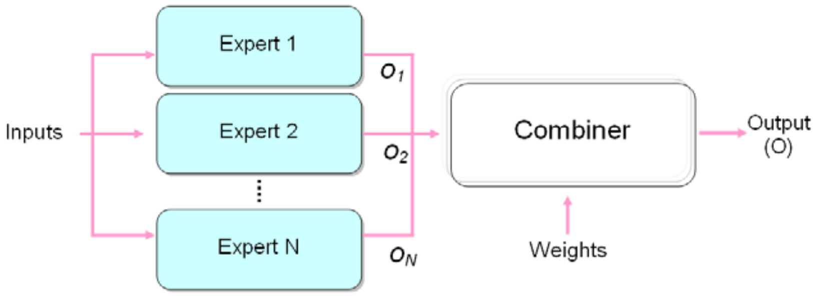

Figure 3: A schematic diagram of a committee machine (Haykin, 1991).

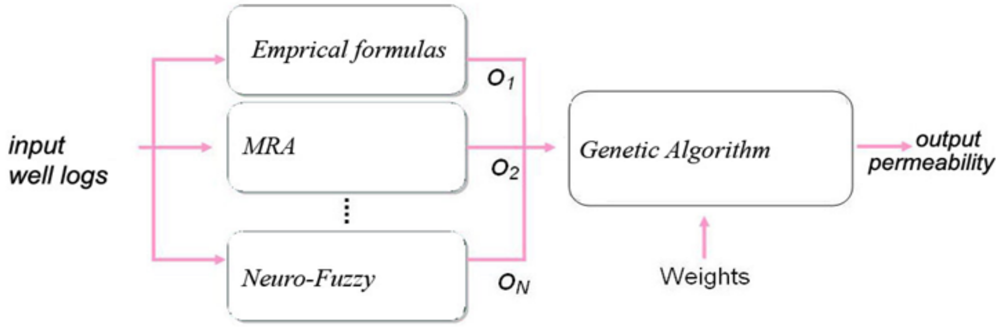

Figure 4: A committee machine used to optimize permeability in this study

Discussion

Case study

Data preparation and processing

The prototype field of this study is the Balal oilfield located in Central part of the Persian Gulf close to the Qatar boarder. Two main reservoirs have been identified in this field: upper Jurassic, Arab Formation (equivalent Surmeh Fm.) and middle Cretaceous, Khatiayah Formation (equivalent Sarvak Fm). The current study is concentrated on the Arab Formation which is composed of a massive bedded anhydrite with varying proportion of limestone and dolomite and clay minerals (Zohorian, 2006).

Well log data including neutron, sonic, density and gamma ray along with core permeability data were used as inputs and outputs of the models. One hundred and fifty-one data points comprising core and well log data from the Arab Reservoir were divided randomly into a training data set with 81 patterns and a testing data set with 70 patterns. The training data were used to obtain the formula coefficients in four empirical formulas, construction of regression formula and construction of NF model. The testing data were used to validate whether the constructed models were robust enough for the unseen data or not. Using the committee machine methodology introduced in this study it is possible to estimate permeability for the other wells that have no role in training and testing procedure.

The data sets were processed and the bad intervals were removed based on deviation between caliper and bit size logs (cutoff=1.5 inch). For correct reading of well log data against core porosity and permeability, the depth matching was carried out.

Permeability prediction

Empirical formulas: The GA derived coefficients for equations 1 through 4 are listed in Table 1. Permeability was estimated using each of the empirical formulas. Comparison between measured and predicted permeability in the test data, using RMSE performance function, showed that Wyllie–Rose formula (Eq. (2)) provided the best estimations than other equations (Table 1). Correlation coefficient between measured and predicted permeability using Eq. (2) is shown in Figure 5a.

Table 1: The GA derived coefficients and performance of empirical formulasused in this study

Formulas	Coefficients	RMSE	R^2
Cateso formula	M=9976.05, D=4.22 ,F=1.94	129.6	0.471
Wyllie–Rose formula	PC=1107.80, PE=5.35, SE=2.19	117.2	0.506
Coates–Dumanior	C=312.59	125.7	0.485
Porosity formula	M=28.10, KC=-2.53	122.0	0.501

MRA: For multiple regression analysis approach, a stepwise regression was used to investigate and model the relationship between permeability (response variable) and conventional well log data (predictors) including neutron (NPHI), sonic (DT), density (RHOB) and volume of shale (V_{sh}). This technique performs stepwise, forward selection or backward elimination which adds or removes variables from a model in order to identify a useful subset of predictors. Estimation procedure was least squares method. The equation of MRA is expressed as below:

$$k = -1.67 - 6556 * NPHI + 6558 * DT + 0.0273 * V_{sh} + 0.375 * RHOB \quad (15)$$

Correlation coefficient between measured and predicted permeability using Eq. (15) is shown in Figure 5b.

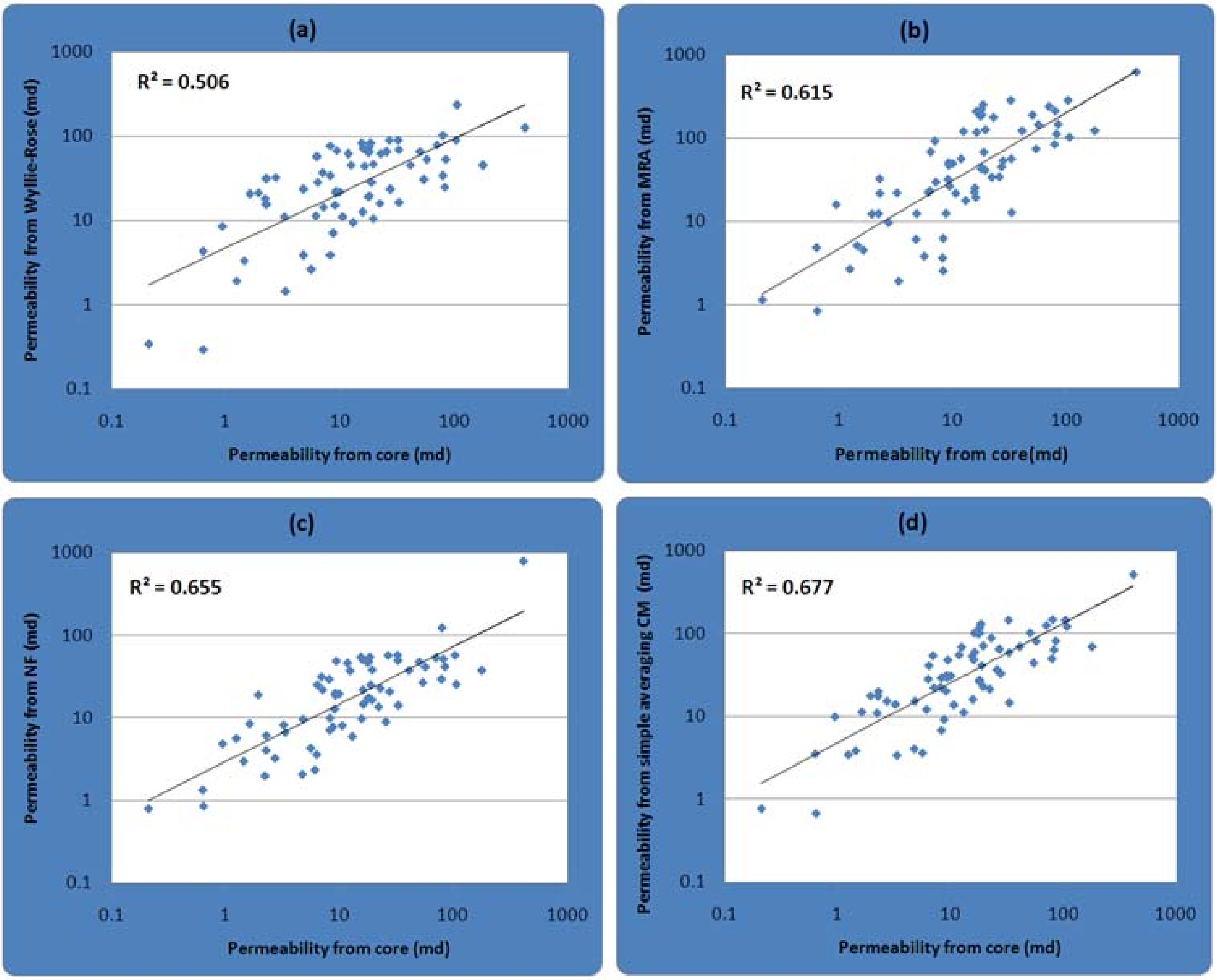

Figure 5: Correlation coefficient between measured and predicted permeability using (a) Wyllie-Rose formula (Eq. (2)), (b) MRA, (c) Neuro-fuzzy, and (d) simple ensemble averaging CM

Neuro-fuzzy: The neuro-fuzzy methodology was used for construction of a model to learn the relationships between well log responses and permeability in training data. Here, an adaptive neuro-fuzzy inference system was used. Three Gaussian membership functions were extracted for each of the inputs and an error-back propagation algorithm was used to adjust their parameters. Figure 6 shows the neuro-fuzzy structure for formulating well log data including NPHI, DT, RHOB, and V_{sh} to permeability data at training data. After 14 training epochs, RMSE performance function was fixed in 0.156. When the training and optimization of the model was finished, the input well log data of the test data were passed to the model and permeability was calculated. Correlation between measured and predicted permeability using NF model is shown in Figure 5c.

CM: In this study, the CM was first constructed by applying simple ensemble averaging method. In this approach, any one of the three methods has equal contribution in constructing

CM. So, in equation 14, $w_1 = w_2 = w_3 = 0.333$. Correlation coefficient between measured and predicted permeability using the simple averaging CM is shown in Figures 5d.

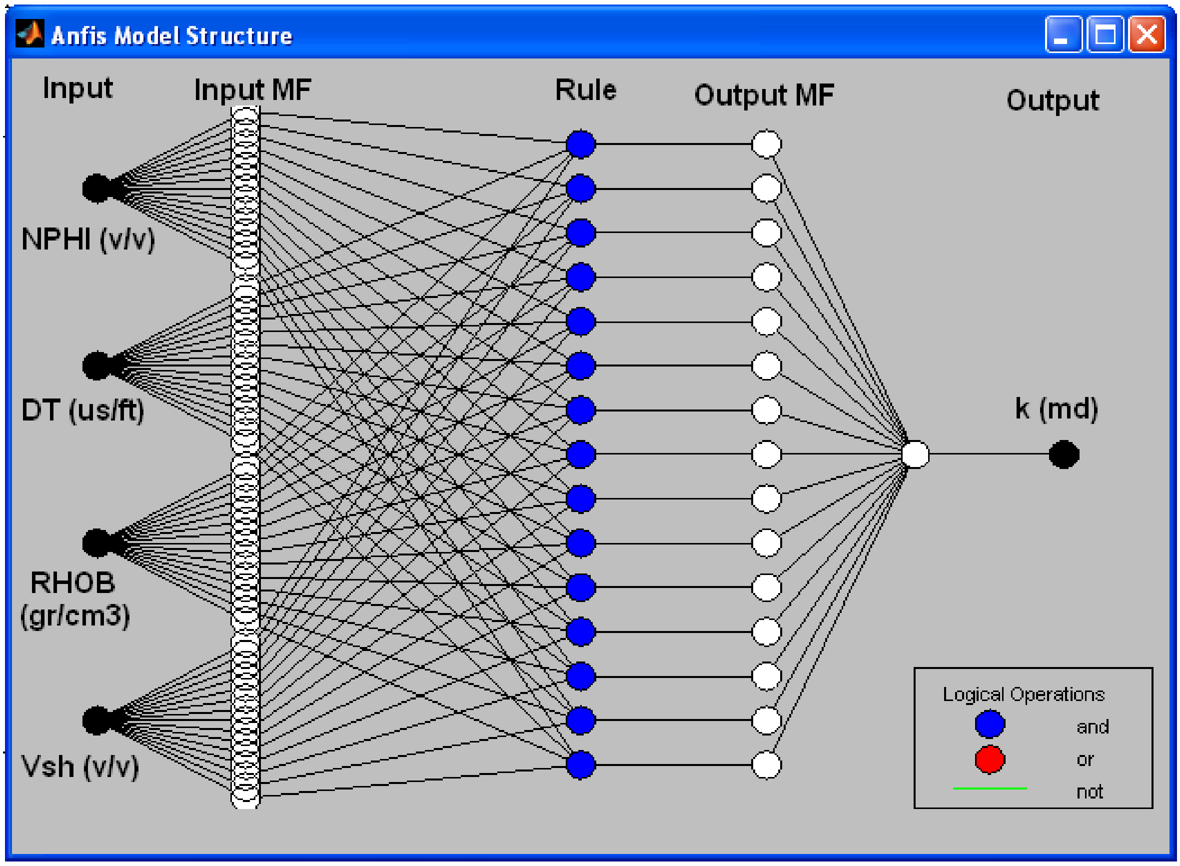

Figure 6: Neuro-fuzzy structure for formulating well log data including NPHI, DT, RHOB, and V_{sh} to permeability

In the next step, a genetic algorithm was used to obtain appropriate weight coefficients of CM in training data. The fitness function which should be minimized by GA was defined as MSE of training data predictions (Eq. 16):

$$\text{Minimize}\quad MSE_{CM} = \sum_{i=1}^{n} 1/n\,((w_1 \times k_{\text{from empirical formula}} + w_2 \times k_{\text{from MRA}} + w_3 \times k_{\text{from NF}}) - k_{\text{measured}})^2 \qquad (16)$$

Where w_1 to w_3 are the weight coefficients corresponding to each algorithm and n is the number of training samples.

Parameter settings for GA are described below. Initial population size is 20 which specifies how many individuals are in each generation and initial range is [0, 1] which specifies the range of the vectors in the initial population. The crossover function is *scattered* and its fraction is 0.8. Mutation function is *Gaussian* that adds a random number, or mutation, from a Gaussian distribution, to each entry of the parent vector. Parameters controlling the mutation are specified as the *scale value* of 1 and *shrink value* of 1. The *scale value* controls the standard deviation of the mutation at the first generation. *Shrink value* controls the rate at which the average amount of mutation decreases. The standard deviation decreases linearly so that its final value equals 1.

According to Figure 7, after 78 generations the mean and best fitness values were fixed in 21.29 and 20.92, respectively. The GA derived values for w_1, w_2 and w_3 are 0.13, 0.22, and 0.65, respectively. Overall estimation of permeability using CM for testing data was calculated as below:

$$k_{CM} = 0.13 \times k_{\text{from empirical formula}} + 0.22 \times k_{\text{from MRA}} + 0.65 \times k_{\text{from NF}} \quad (17)$$

Correlation coefficient and a comparison graph between measured and predicted permeability using the GA optimized CM are shown in Figures 8 and 9, respectively.

In Table 2, a comparison of RMSE for predicting permeability in testing data points, using different methods including empirical formula, MRA, NF and CM (averaging method), and CM (GA optimized), is shown. Considering crossplots of Figure 5 and Table 2, the simple averaging CM has provided the smaller error (43.9) in comparison with the best empirical formula (117.2), MRA (85.3) and neuro-fuzzy (51).

Table 2: Comparison of RMSE for permeability estimation using different methods.

Method	RMSE	Rank
Wyllie-Rose formula	117.2	5
MRA	85.3	4
NF	51.0	3
CM (averaging method)	43.9	2
CM (GA optimized)	41.2	1

RMSE of the GA optimized CM for the test data is 41.2 which corresponds to the R^2 value of 0.706 (Figure 8).

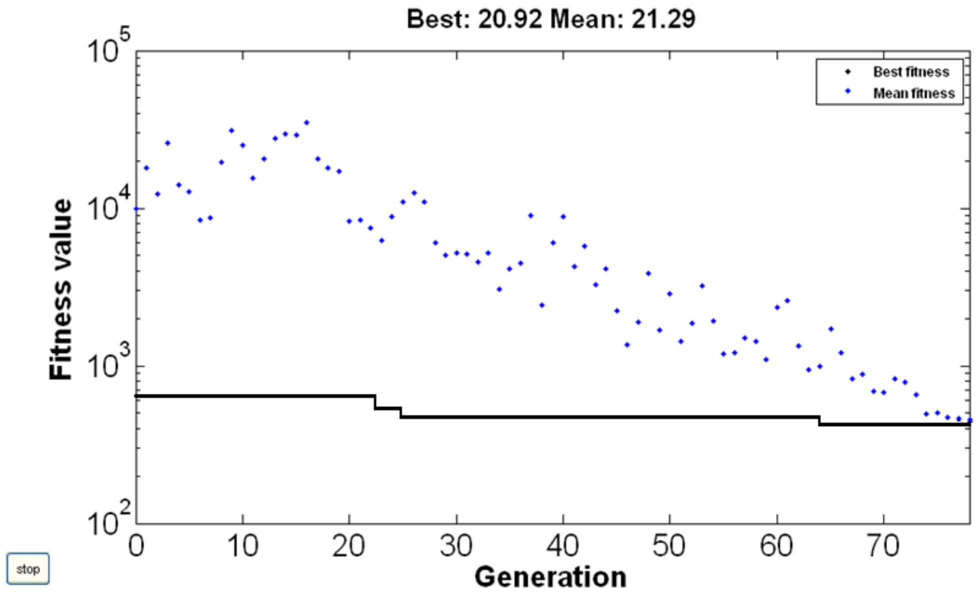

Figure 7: Mean and best fitness values of fitness function after 78 generations

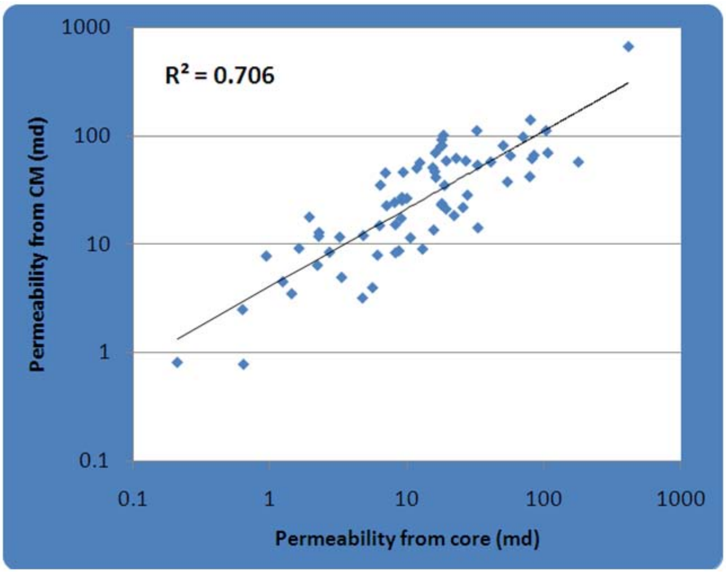

Figure 8: Correlation coefficient between measured and CM permeability (Optimized by GA).

This indicates that CM has had some improvement for the estimation of permeability from well log data. Namely, CM performs better than any one of the individual methods acting alone for permeability predicting problem. Also it has provided better results than constructed CM by simple averaging method.

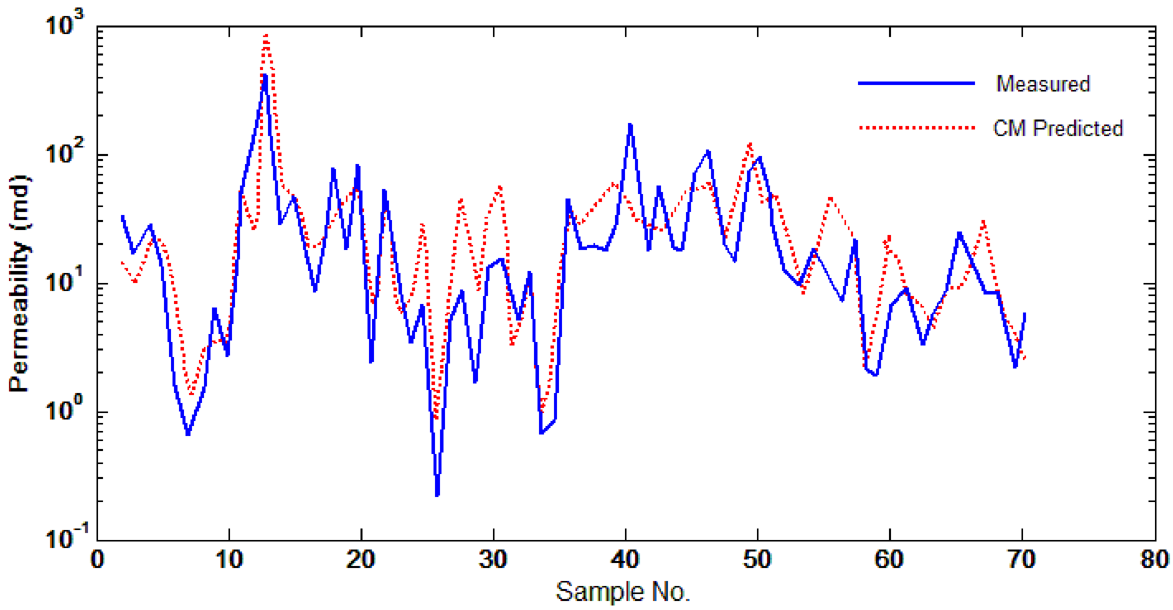

Figure 9: A graphical comparison between measured and CM permeability (Optimized by GA) in the test data.

Conclusions

In this paper, a committee machine (CM) was developed for the estimation of permeability from well log data in the Balal Oil Field, Persian Gulf. In the test data, the performance of genetic algorithm optimized CM was excellent compared to other individual methods including empirical formulas, multiple regression analysis, neuro-fuzzy and averaging based CM. The CM approach is simple to use and easy to implement, and it provides some improvement in permeability prediction.

The CM is expected to provide more accurate results than other techniques for the studied field where core data are not available.

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