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# Application of Committee Machine Neural Networks Utilized with Fuzzy Genetic Algorithm (FGA CMNN) in Prediction of Permeability: A Case Study from the Rag-e-Sefid Oilfield, Iran

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**Abstract.** Wide range of permeability variations in a reservoir restricts accuracy of its estimation by artificial neural networks (ANNs). Many models have been proposed to mitigate this problem among which a committee machine neural network (CMNN) seems to be the most effective one, in which a combination of neural networks (experts) will improve the performance compared to single constituent networks in isolation. As an ordinary method of combination, the weighted average of the outputs of constituent experts is considered to be the final output of the presented CMNN. These weights are usually calculated using genetic algorithm (GA). In the present work a Fuzzy Gendered Genetic Algorithm (FGA) method is presented to calculate the so called weights. In this method the GA generations are divided randomly into male and female chromosomes. Each member of a selected male chromosome group is labeled based on its fitness value then the appropriate female chromosome, for recombining with that male chromosome, is selected based on the male chromosome label and the population diversity of the previous generation, using a set of fuzzy rules. Finally by comparing the results of the proposed FGA CMNN with those of traditional back propagation neural network (BPNN) the predominance of FGA CMNN over a single BPNN is concluded.

**Keywords:** committee machine, neural networks, fuzzy genetic algorithm, permeability prediction, fuzzy logic, genetic algorithm.

## 1. Introduction

Reliable prediction of permeability and finding its spatial distribution throughout the reservoir is of crucial importance from the reservoir management and EOR design point of view. Although no petrophysical procedure is designed for direct measurement of permeability so far, however as a common practice in industry, correlating well logs with permeability obtained from analyzing core samples in cored wells using ANNs seems to be a good method that can be performed with limited core and wireline log data. However individual ANNs cannot predict permeability as accurate as other petrophysical properties in many cases. This problem emerges from the fact that permeability is a highly heterogeneous property and varies significantly even within small intervals in the borehole. To solve this problem the learning task is distributed among a number of individual networks working together in a committee to improve the generalization ability. The combined group of ANNs (experts) in which each expert performs a different task is called a Committee Machine Neural Network (CMNN). The final result depends on the method of creating experts and combining their results.

The present work is a comparative study in which a novel type of CMNNs in combining experts known as Fuzzy Genetic Algorithm (FGA) CMNN proposed by Jafari et al. [1] is used to train our CMNN to predict permeability and its results will then be compared with those of traditional back-propagation neural networks

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(BPNN) in terms of $R^2$ using the same input dataset. Next sections provide detailed description of the CMNNs and the FGA model of combining experts.

# 2. Artificial Neural Networks

## 2.1. Traditional Back-Propagation Neural Networks

A BPNN neural network consists of an input layer, an output layer and at least a hidden one. When a normalized presentation of the input (or outputs of the 'previous' layer) data $x$ with $i$ signals is fed to the input layer (or 'current' layer), each neuron receives the sum of the weighted input signals and passes it to an activation function that produces the output signal. Then by computing the difference between the calculated output ($y$) and the corresponding desired output ($T$) from the training data set and propagating the error backward through the network using a training algorithm performance function (error function) the BPNN weights are modified. After a number of iterations the training stops when the calculated output values best approximate the desired values. In this study, several training algorithms are used to train the traditional BPNN. Detailed description of these algorithms can be found elsewhere.

## 2.2. Committee Machine Neural Networks

A committee machine uses a "divide and conquer" strategy in which the outputs of multiple experts are combined through a combiner into a single output using different combination methods such as simple averaging (Fig. (1.a)) . This output is superior to those of its constituent experts and results in better generalization and performance [3].

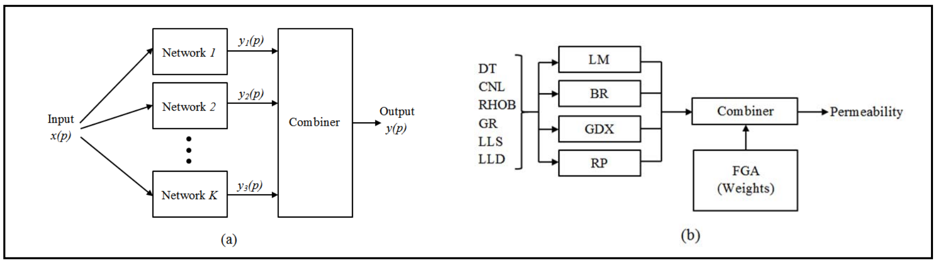


Fig. 1: (a) Schematic of a committee machine and (b) the CMNN designed in this study.

### 2.2.1. Combination methods

The final stage of designing a CMNN is defining the combiner. Other than simply averaging method there are other common combining methods such as weighted averaging method in which every expert has a suitable weight which can be determined using Genetic Algorithm. The choice of combination method mainly depends on the characteristics of the particular application that we have in hand, e.g. the nature of the application (classifier or regression), the size and quality of the training data and the generated errors on the region of the input space [1]. In this paper we have used a combination method known as Fuzzy Genetic Algorithm (FGA) proposed by Jafari et al. [1] to perform our case study. Next section presents a brief description of this combining method.

#### 2.2.1.1. Fuzzy genetic algorithm (FGA) combiner

In an FGA combiner a gendered GA model is used to find the optimum weight of any expert to perform weighted averaging method. In contrast with the classical GA models in which chromosomes reproduce asexually (randomly), in gendered GA model the crossover takes place only between chromosomes of an opposite sex. In an FGA combiner the population is divided into two groups, male and female. During recombination, the male chromosomes are randomly selected. Then the fitness of each male chromosome is used to calculate it's 'age' using a bi-linear allocation lifetime approach [2]:

$$\left.\begin{aligned}\varphi &= \frac{f_i - f_{\min}}{f_{ave} - f_{\min}} \\ \phi &= \frac{f_i - f_{ave}}{f_{\max} - f_{ave}} \\ \tau &= f_{ave} - f_i\end{aligned}\right\} \Rightarrow age(c_i) = \begin{cases}(L + \alpha\varphi)/n & \tau \geq 0 \\ (\beta + \alpha\phi)/n & \tau < 0\end{cases} \qquad \text{Eq. (1)}$$

Where $f_i$=fitness value of $i$-th chromosome, $f_{avr}$=average fitness value, $f_{min}$=minimum fitness value, and $f_{max}$=maximum fitness value of the population, $c_i$=$i$-th chromosome, $L$=minimum age, $U$=maximum age, $n$=Population size, $\alpha$=($U$+$L$)/2 and $\beta$=($U$-$L$)/2. For the FGA combiner $L$=2 and $U$=10. Then the chromosome age is used as a linguistic variable to label chromosomes in terms of 'Infant', 'Teenager', 'Adult' and 'Elderly' linguistic values. This computation takes into account all chromosomes in each generation and relies on the triangular membership functions (Fig. (2.a)). Defuzzification of the outputs is performed using the fuzzy centroid method described by Kosko [2]. Then the Kosko bi-linear allocation lifetime approach is used again, this time to calculate each chromosome's diversity factor ($D(c_i)$) based on their fitness:

$$D(c_i) = \begin{cases}(L + \alpha\varphi) & \tau \geq 0 \\ (\beta + \alpha\phi) & \tau < 0\end{cases} \qquad \text{Eq. (2)}$$

Then the chromosome diversity factor is used as a linguistic variable to label chromosomes. This computation takes into account all chromosomes in each generation and relies on the triangular membership functions (Fig. (2.b)).

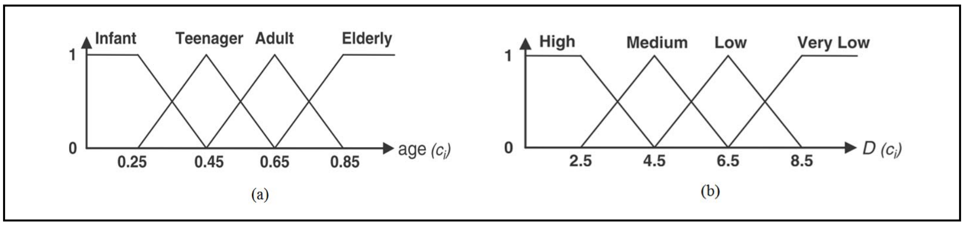


Fig. 2: (a) The age linguistic variables for male and female. (b) The PD linguistic variables.

Now let $\psi$=diversity label of half of the population, then the population can be divided into four levels of population diversity (PD): Very Low, Low, Medium and High as follows ([$x$] means nearest integer number to $x$):

$$t = [[\frac{n}{10}] \times (\frac{L+U}{n})] \quad \Rightarrow \quad PD = \begin{cases}High & \psi \leq L + t \\ Medium & L + t < \psi \leq L + t + 1 \\ Low & L + t + 1 < \psi \leq L + t + 2 \\ Very\ \ Low & \psi > L + t + 2\end{cases} \qquad \text{Eq. (3)}$$

Finally the age label of the selected chromosome and the PD of the previous generation are applied within a set of fuzzy rules tabulated in Table (1) to select a suitable female chromosome in terms of the female age ($F_{age}$). The detailed description of defuzzification process can be found elsewhere [2]. The female chromosome that has the exact $F_{age}$ may not be found. So a female chromosome having the nearest fitness value to $F_{age}$ is selected to be the parent [1].

Table 1: Fuzzy rules for selecting female chromosome.

| **Male Age** / **PD** | Infant | Teenager | Adult | Elderly |
|---|---|---|---|---|
| High | Elderly or adult | Elderly or adult | Elderly or adult | Adult or teenager |
| Medium | Adult or teenager | Adult or teenager | Adult or teenager | Teenager or infant |
| Low | Teenager or infant | Teenager or infant | Teenager or infant | Infant |
| Very Low | Infant | Infant | Infant | Infant |

# 3. Results and Discussion

## 3.1. Preparing appropriate input data

The data used in the current study are prepared from petrophysical and core plug data collected from 3 wells in the Rag-e-Sefid (RS) oil field located in Khuzestan province, southwest Iran. These wells have a full set of wireline log data from the borehole in Asmari formation interval among which digitized sonic (DT), neutron (CNL), density (RHOB), Gamma ray (GR) and resistivity (LLS and LLD) wireline log data are selected based on their correlation coefficient (R2) with depth matched core permeability. Also a cross-correlation between core and well-logging data should be performed to match them in depth. Needless to say, permeability of core samples is used as our committee machine target.

## 3.2. Constructing experts

The reservoir permeability varies in a wide range from $10^{-3}$ to $10^{+3}$ millidarcy. This range needs many of the input data for training to be accomplished, which is not possible with our limited data. Here we follow the work of Karimpouli et al. [4]: Plotting the log-log graph of cumulative percent of number of core samples versus normalized permeability (Fig. (3)), 4 different statistical populations of permeability are found in the primary data and are considered as populations with Low, Intermediate, High and Very High permeability zones. The t-Student's distribution test also can be performed to ensure that these populations are far apart. In contrast with the work of Karimpouli et al. [4] in which they have used classified data in a supervised manner to train their Committee Machine with Divide and Conquer (CMDC), here we classified data in order to construct our CMNN in an efficient way with optimum number of experts, each one is a BPNN with different training algorithm, because low number of experts may result in poor estimation and high number of them will significantly increase the CPU time to perform training [4]. Because we have 4 populations of permeability our CMNN consists of 4 experts to better estimate 4 different behaviors of permeability: Levenberg-Marquardt (LM), Bayesian Regulation (BR), Gradient Descent with Momentum and adaptive Learning rate (GDX) and Resilient Back Propagation (RP) as shown in Fig. (1.b).

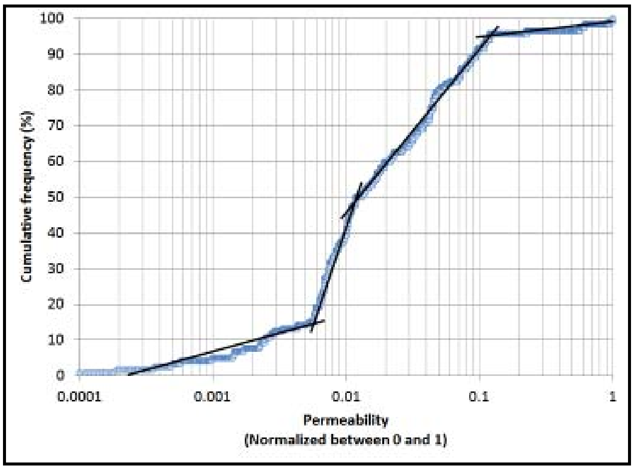


Fig. 3: Cumulative percent plot of number of core samples versus permeability.

## 3.3. Committee machine construction using FGA

To construct FGA CM, first the FGA method is used to obtain optimal weights for combining the results of experts. The fitness function for FGA is defined as [1]:

$$MSE_{FGA} = \frac{1}{n}\sum_{i=1}^{n}\left(\sum_{j=1}^{K} w_j y_{ji} - T_i\right)^2 \qquad \text{Eq. (6)}$$

In this function, $y_{ji}$ are the outputs of j-th expert and Ti is the target value of the $i$-th input, and $n$ is the number of training data. As stated before the population is divided into two groups, male and female. Then a proper female chromosome is found by applying age label of the selected male chromosome and the PD of the previous generation within a set of Fuzzy rules (Table (1)). The K-Point and Random number (KPR) method [5] is then used for performing the crossover process. Then a random real number from an interval (0, 1) is generated for the probability of mutation. GA selects some chromosomes based on this probability and for all of them a random natural number $k$ (here $k$=2), varying from 1 to the number of genes in the chromosome is generated. Finally the gene number k is replaced by another randomly-generated gene to perform the mutation. Here we used a standard GA configuration defined by DeJong and Spears [6] in which population size = 30, total length of the chromosomes = 85 bits, crossover probability = 0.6, mutation probability = 0.001, with a maximum of 3000 generations. It's been found that increasing PD and male's age will decrease the age of suitable female chromosome. So PD is maintained and GA cannot converge very soon, and premature convergence will be avoided [1]. As mentioned earlier, in order to compare the results of predicting permeability with FGA CMNN and those of traditional ANNs, we have used wireline log data and core permeability of 90 core samples (30 samples per well) to train our networks. As shown in Table (2), using FGA CMNN approach results in more R2 in comparison with classical BPNN with LM, BR, GDX and RP training algorithms. Fig. (4.a) shows the best correlation coefficient obtained between the core and FGA CMNN predicted permeability for well number 2. The reason that this value is smaller in other wells is that the core permeability varies in a wider range for those wells. Fig. (4.b) shows the actual permeability values that were measured in the laboratory in comparison with the CMNNs prediction for each core sample in well number 2.

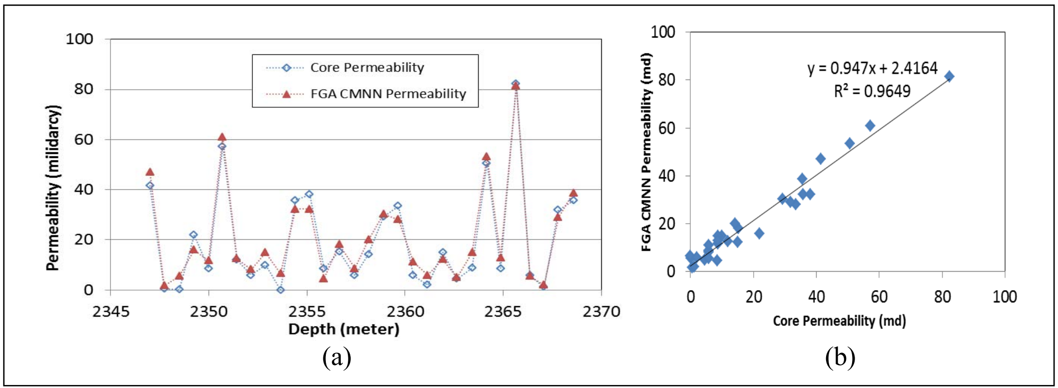


Fig. 4: (a) Mapping of permeability obtained by CMNN and core permeability and (b) CMNN permeability versus core permeability for well number 2.

| | BPNN with LM | BPNN with BR | BPNN with GDX | BPNN with RP | FGA CMNN |
|---|---|---|---|---|---|
| Well # 1 | 0.8935 | 0.8472 | 0.8396 | 0.7947 | 0.9327 |
| Well # 2 | 0.9244 | 0.9056 | 0.8395 | 0.8074 | 0.9649 |
| Well # 3 | 0.8721 | 0.8354 | 0.8041 | 0.7623 | 0.9084 |

Table 2: $R^2$ in predicting permeability with classical BPNN with LM, BR, GDX and RP training algorithms and FGA CMNN.

## 4. Conclusions

In this paper, a committee machine neural network (CMNN) was developed for the estimation of permeability from wireline log data in 3 wells in Rag-e-Sefid oilfield. The main idea is to use a combination of networks rather than a single network that cannot cover the wide range of permeability variations properly. This CMNN consists of 4 back-propagation neural networks (experts) each with different training algorithm. Then a fuzzy genetic algorithm method is used to obtain the contribution of experts in the overall output of the CMNN by assigning a weight factor to each expert. So the overall output is the weighted average of the outputs of constituent experts. The results of the permeability estimation indicate the predominance of CMNN over single constituent BPNNs in terms of $R^2$.

## 5. References

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