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PREDICTING PERMEABILITY OF RESERVOIR USING COMMITTEE NEURAL NETWORK

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ABSTRACT

Permeability is an essential petro-physical property required to efficiently characterize a reservoir. Since it is a complex function of several interrelated factors such as lithology, pore fluid composition and porosity; it varies significantly within the formation. The routine and economic procedure in the oil industry has been to estimate it from well logs using empirical equations (EE). Artificial neural networks have emerged as a data driven tool that has ability to map complex statistical relationship between data; such as relation between well-log and reservoir properties.

*In this study, seven (7) multiple-layer perceptron (MLP) networks were trained using well logs as input data and core data as output data in MATLAB neural network toolbox. The best four (4) MLPs, called expert networks (EN), were selected and combined to form committee network (CN). The committee network fused knowledge by combining the individual outputs of the experts to arrive at a better overall output. Since core data gives the best permeability, the correlation coefficients obtained between core data and the respective CN, EN and EE methods was **0.89: 0.71: 0.61**. Clearly, the correlation values for CN and EN gives a better prediction of the core permeability compared to EE.*

1. INTRODUCTION

Characterizing a reservoir entails estimating different petro-physical properties of the subsurface which are mainly responsible for the presence of hydrocarbon. Permeability is one of the key parameters used to evaluate a reservoir. It is a measure of the ease with which fluids can flow through pore spaces in the formation. Depending on the available data, permeability can be determined by analysing well test data, core data, or well log data. Since core and well test data are expensive to acquire, most times petro physicist estimate permeability from well log using location dependent empirical equations like Kozeny-Carman or Wyllie and Rose [1, 2]. However, these methods are complex and prone to error because it requires expert knowledge, consultation of reference chart, adjustment of parameter in empirical equations and cross plot between different logs.

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With advancements in artificial intelligence and high-performance computing, geoscientists and reservoir engineers can acquire large volume of data; which once analysed can be used to build complex models of the reservoir in a timely manner [3]. The advent of big data ushered in the era of data-driven methods for formation evaluation. Neural network is one of the data driven method, which leverages on available large datasets to extract patterns, relationships, and insights about subsurface reservoirs. Although these methods serve to complement the traditional tools used for formation evaluation, they are efficient and produce accurate results, which guides professionals to make informed decision during hydrocarbon exploration and production [4].

Neural Networks grew out of research in artificial intelligence (AI) in an attempt to create artificial neurons which has the capacity to learn like biological neurons in the human brain [5]. Since neural network is designed to mimic biological learning processes as it occurs in human brains, it possesses capacity to learn complex relationships between data when trained, therefore they are suitable for cognitive problems like: pattern recognition/association, function approximation and classification [6]. A typical neural network consists of parallel and distributed interconnection of artificial neurons organized in layers: input layer (i), one or more hidden layers (h) and output layer(o) shown in figure 1

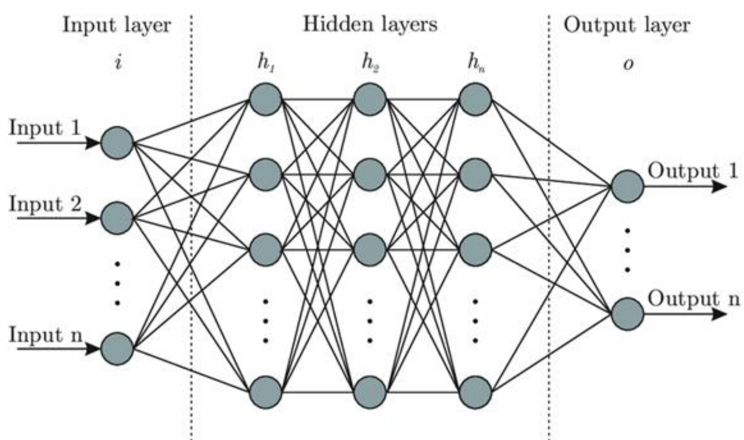

Figure 1: A typical neural network architecture

The input layer only serves as a terminal to provide input signals to the network, actual computation is carried out in the hidden and output layers. The artificial neuron, which is the basic computational unit is modelled like the biological neuron as shown in in figure 2.

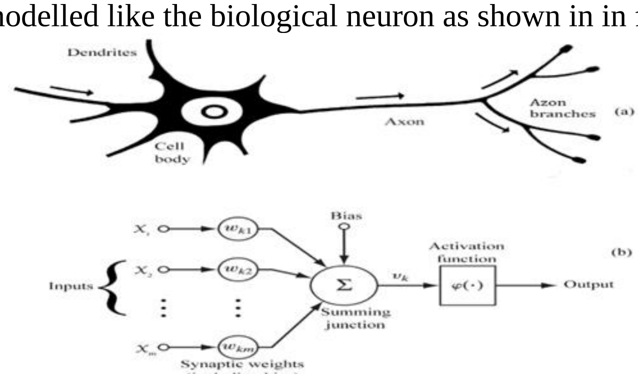

Figure 2: Comparism of (a) biological neuron (b) artificial neuron

The mathematical model of an artificial neuron shown in figure 3 computes the weighted sum of all the input signals along with the connected bias and pass it through an activation function to produce the output signal.

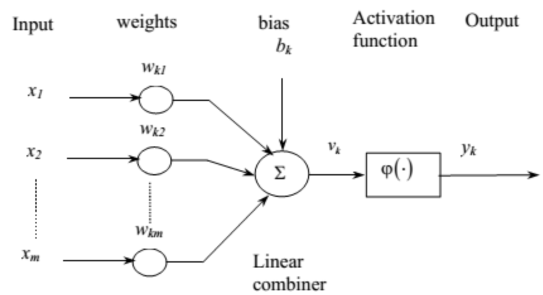

Figure 3: Mathematical model of artificial neuron

When inputs $x_1, x_2, x_3 \ldots x_m$ of synaptic weight $w_{k1}, w_{k2}, w_{k3} \ldots . w_{km}$ enters the neuron k, then the combined input at the neuron k (which is the sum of the product of the input and the associated weight) becomes:

$u_k = \sum_{j=1}^{m} w_{kj}\, x_j$ (1)
Let $v_k = (u_k + b_k)$ (2)
Suppose the bias is be taken as input, Such that $b_k = w_{k0}$
$y_k = \varphi(v_k) = \varphi(v_k + b_k)$ (3)
$y_k = \varphi\{\sum_{j=0}^{m} w_{kj}\, x_j\}$ (4)

Where $x_j$the input is signal from a m-dimensional input space, w_{kj} is the synaptic weight of neuron k, u_k is linear combiner of all incoming signal, $\varphi(.)$ is the activation signal and v_k is the activation potential. b_k is the bias and y_k is the output signal.

The two (2) basic types of neural network are: feed forward network (the neurons in different layers are connected such that signal flow from the input to output in a forward manner) and recurrent network (the neurons in different layers are connected such that there are feedback loop(s) between neurons in the network). The architecture of any network is defined by the number of layers, number of neurons in the layers, the activation function (in each layer), the learning function and the training function.

A Committee Network (CN) is made up of two or more candidate networks, often called expert networks (EN) that are joined together. The ENs are created by varying the type and architecture of the networks, training them differently and then combining their outputs. The expectation is that the differently trained experts converge to different local minima on the error surface, and the overall performance is improved by combining their outputs in some way [1, 7]. Figure 4 is a CN consisting of four (4) multiple layer perceptron (MLP) network.

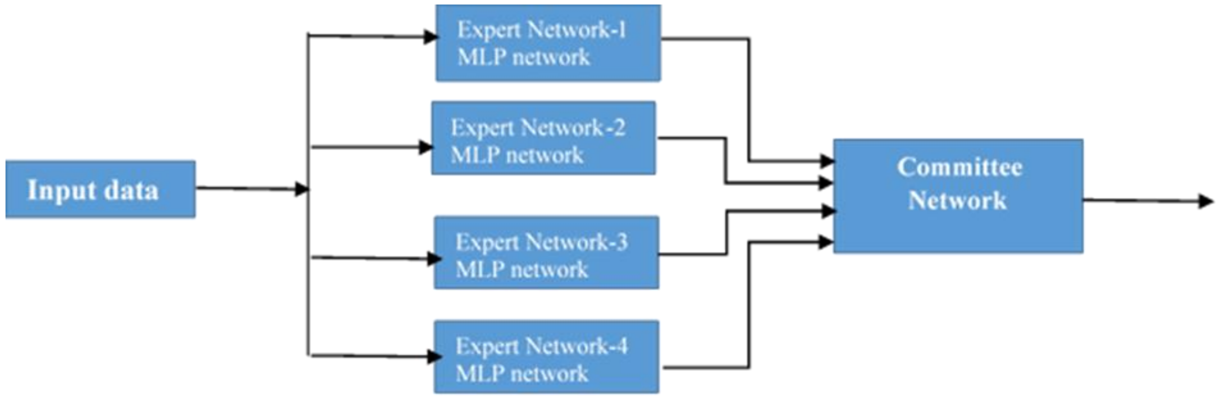

Figure 4 Committee Network

2. LITERATURE REVIEW

Petroleum reservoir are heterogeneous and complex; therefore, permeability varies within the formation, often displaying recognizable pattern [8]. Data driven method like neural network has become popular in the domain of reservoir characterization due to its ability to map complex non-linear relationships between log-core data [4, 9]. Modern reservoir characterization has evolved from the use of experts to analyze and interpret log data to the application of artificial intelligence to automatically identify patterns [10].

Neural network has been applied extensively to predict permeability of reservoir. [9] applied a 4-12-3 feed-forward neural network architecture to predict porosity, permeability and water saturation using depth, gamma log, resistivity log and density log as input data. Machine learning technique like stochastic gradient boosting (SGB) regression model has been applied to predict the permeability of petroleum reservoirs based on well logs [11]. Support vector machine (SVM) a variant of neural network was deployed to predict the permeability of gas wells. The result obtained showed a 97% correlation coefficient between core and predicted permeability [12].

Recent works on reservoir characterization showed that combining neural network with other intelligent models such as: Artificial Neural Network-Genetic Algorithm (ANN-GA) system, provided enhanced models with better performance and precision than the conventional ANN models [13, 14]. [15] deployed a committee network consisting of Radial Basis Feed Forward Network (RBFNN) and Genetic Algorithm (GA) to predict permeability. Multiple layer perceptron (MLP), radial basis function (RBF) and generalized regression neural network (GRNN) were combined as committee network and used for predicting permeability from well logs [16].

The common practice in petroleum industry is to calculate permeability from well logs using empirical equations, then compare the result to available core data obtained from laboratory analysis. In this study, an attempt is made to present neural network as an alternative tool to characterize a reservoir, by training a committee network to predict the permeability using well logs as input data and core as output data.

3. METHODOLOGY

The well logs and core data for two (2) wells (labelled well-A and well-B) used in this study was sourced from Shell Petroleum Development Company (SPDC). In addition to the well log and core data, the calculated permeability for both wells was supplied. Although the equation used for the calculation was undisclosed, this data will be taken as permeability gotten from Empirical Equation (EE).

In conducting this study, four (4) steps were employed: (i) data preparation and processing (ii) creation and training of candidate networks (iii) selection and training of expert networks as committee network (iv) prediction of permeability with best expert network and committee network and comparing predicted permeability with core and empirical equation derived data.

Step 1: Preparation and Processing of Data

The well logs (density, sonic, neutron and gamma) served as input data while permeability core data was used as output data. Well-A dataset was used for training while well-B dataset was deployed to test generalization of the trained networks. Usually, a depth mismatch exists between the well logs and the core data due to the different sampling depths within the formation. This can be resolved by carrying out log-core calibration by averaging over same range of depths, depth-shifting well log by visual comparison and repositioning core [17, 14]. Table 1 represents the range of values for core permeability before and after log-core calibration. Both data sets were processed using ***mapminmax*** processing function in MATLAB neural network toolbox. This processing function maps the data within the range [-1, 1] in order to speed up the training process [18]. Table 1 shows the value of core permeability before and after log-core calibration.

Table 1 Core permeability before and after log-core calibration.

	Range of value before log-core calibration	Range of value after log-core calibration
Core Permeability (mD)	720-2315	550-2198

Step 2: Creating and Training the Network

Seven (7) candidate feed forward Multiple Layer Perceptron (MLPs) were created. Each MLP network had 2-layers, sigmoid and linear functions were used as the activation functions in the hidden and output layers respectively. In order to create unique MLPs with different learning capacities, the number of neurons in the hidden layer for each MLP was varied between 20-30 neurons [19]. Figure 5 shows the network architecture of one of the MLP.

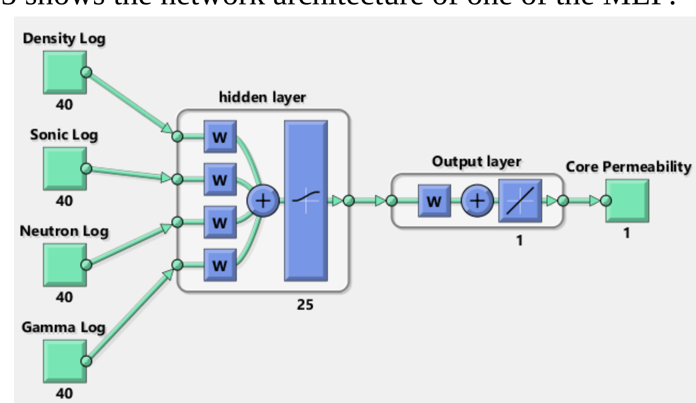

Figure 5 Network Architecture of one of the MLP

The well-A dataset was divided into 2-parts: 70% (training data) and 30% (testing data). The 7-candidate MLPs were randomly initiated and trained several times using the 3-diferent training functions namely: Levenberg-Marquardt (***trainlm***), resilient back propagation (**trainrp**) and scaled conjugate gradient backpropagation (**trainscg**).

Step 3: Selection of expert networks to form committee network

After training, each of the 7-MLPs was tested to evaluate their ability to generalize for unseen data. The extent to which each network generalized was determined using the ***plotperformance*** and ***plotregression*** functions in the toolbox. The 4-MLPs which had the least mean squared error and highest coefficient of regression were selected as expert networks (EN) and joined together form committee network, then retrained. The output of the committee network was computed using method of ensemble averaging.

Step 4: Prediction of permeability with committee network and comparism of permeability values

The unseen well-B dataset was used to test the capacity of the EN and the CN to predict permeability of the reservoir. Since core data was obtained directly from formation and is considered to produce the best permeability value. The extent to which the permeability values gotten by Committee Network (CN), best expert network (EN) and the Empirical equation (EE) matched the core permeability was determined by plotting the *Pearson* correlation between core permeability and respective permeability values obtained by each of the 3-methods: CN, best-EN and EE.

RESULTS AND DISCUSSION

4.1 Criteria to determine performance of network

During training, the performance of the network was evaluated by the error between the predicted output of the network and the actual output (or target value) for an individual set of input data. The calculated error over the entire set of data was evaluated using the cost function. The mean squared error (MSE) was used as cost function in this study. Once a potentially suitable network was chosen depending on the value of the MSE, it is tested with the unseen well-B dataset, the extent to which the network can generalize is calculated by the coefficient of regression (R) obtained between the target data and network predicted output. Table 2 is the performance and correlation criteria for accepting or rejecting trained and tested MLPs, and expert networks (ENs).

Table 2 Correlation and Performance criteria used to choose MLPs and ENs

Parameter/ Description	Poor Network	Good Network	Excellent Network
Correlation Coefficient (R) (Plot of the target value versus the network predicted output during testing. This is obtained using the ***plotregression*** functions. It shows the ability of the trained network(s) to generalize for unseen test data)	0.00-0.49	0.50-0.79	0.80-1.00
Performance (Plot of mean squared error (mse) versus epoch during the training session. This is obtained using the ***plotperformance*** functions. It shows the performance of the network.	0.1-0.01	0.001-0.01	0.0001-0.001

4.2 Selecting 4-expert networks from the 7-MLPs

Density, sonic, neutron and gamma logs were used as input data while core permeability was used as the target (output) data for the 7-MLPs. They were configured with different number of neurons in the hidden layer and trained simultaneously several times. Three (3) different training function were used: Levenberg-Marquardt (***trainlm***), resilient back propagation (**trainrp**) and scaled conjugate gradient backpropagation (**trainscg**). After, training, the well-A dataset was used to test the network. The ***trainlm*** produced the optimal network with the best generalization.

Table 3, shows the performance, correlation coefficient and the rank for the 7-MLPs. This table helps us to decide which MLPs had better correlation between the actual data and network predicted output. Based on the criteria in Table 2, a suitable network should have a minimum correlation coefficient (R=0.5) and minimum mean squared error (e<0.001). Figure 6 is the regression plot of the actual permeability versus network predicted permeability for each MLP when tested (with the 30% testing data from well-A dataset). MLPs with higher regression coefficient are considered to have produced better generalization.

Table 3 network Performance, coefficient of correlation and ranking for the 7-MLPs

NETWORK	PERFOMANCE (MSE)	Correlation coefficient (R)	RANK (highest to smallest)	COMMENT Network selected as Expert Network (EN)
MLP-1	0.00076	0.578	6	2nd
MLP-2	0.00081	0.554	5	3rd
MLP-3	0.00092	0.485	4	4th
MLP-4	0.00761	0.353	2	
MLP-5	0.01575	0.003	1	
MLP-6	0.00045	0.650	7	I st (Best-EN)
MLP-7	0.00450	0.547	3	

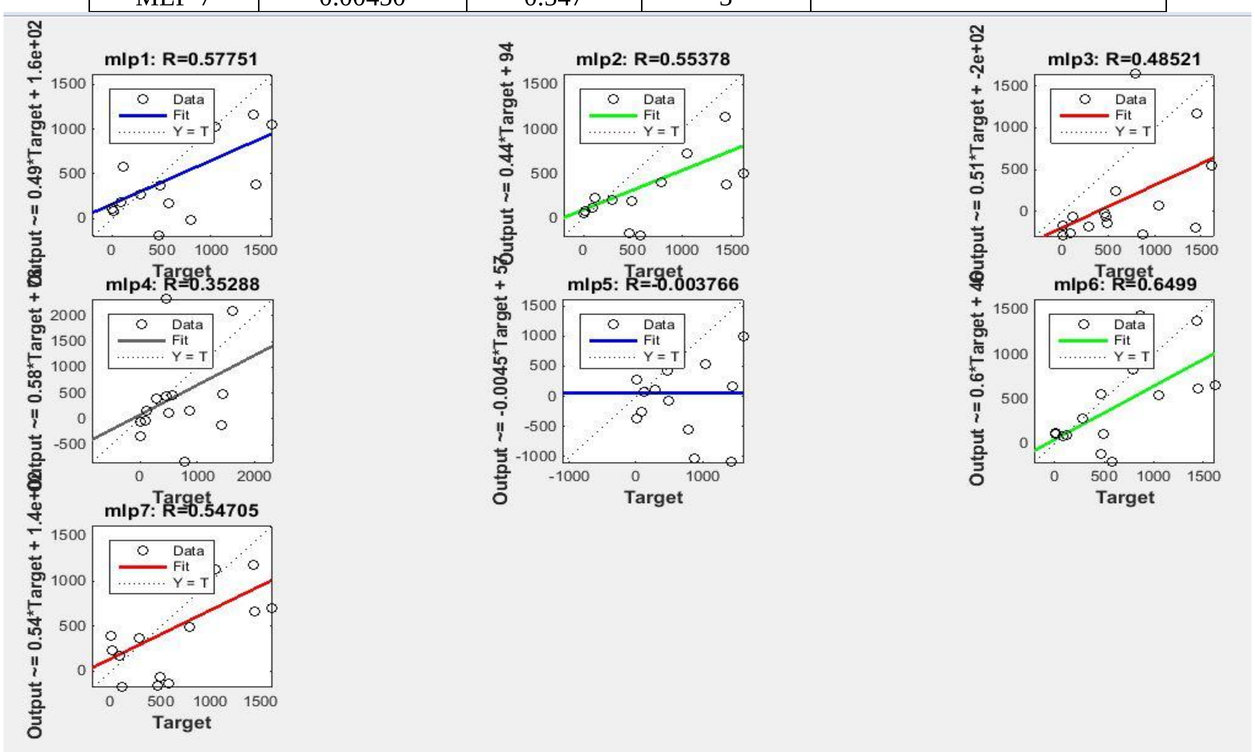

Figure 6: Plot of correlation coefficient for the 7-MLPs

4.2 Selecting 4-expert networks from the 7-MLPs to form committee network (CN)

The ranking of the network performance is based on the degree of correlation between the actual (core) permeability and network predicted permeability. This means that as $R \to 1$, the trained MLP give better generalization for unseen data. From table 3, MLP-6, MLP-1, MLP-2 and MLP-3 were taken as the expert networks (EN). These ENs were retrained several times using ***trainlm function*** to obtain the best network parameter, and their outputs were combined by simple averaging method to form the committee network (CN).

Table 4 helps us to see the performance, correlation coefficient and the rank for the ENs while figure 7 is the regression plot of the actual permeability versus network predicted permeability for each MLP when tested (with the 30% testing data from well-A dataset).

Table 4 Network Performance, coefficient of correlation and ranking for the 7-MLPs

NETWORK	PERFOMANCE (MSE)	Correlation coefficient (R)	RANK (highest to smallest)	COMMENT
CN	0.00026	0.894	5	Best network
EN-1	0.12570	0.001	1	
EN-2	0.00075	0.708	4	
EN-3	0.00458	0.507	2	
EN-4	0.00094	0.649	3	

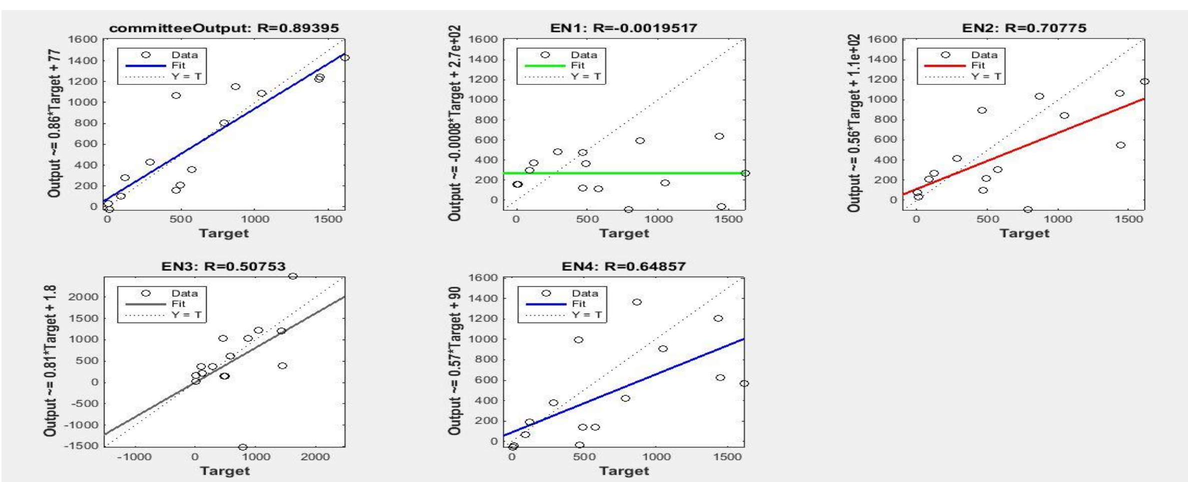

Figure 7: Plot of correlation coefficient for the 4-ENs and the committee network (CN)

4.3 Predicting permeability with Committee Network and comparing permeability values

The well-B dataset data was used to test the ability of both committee network (CN) and the best-expert network (best-EN) to effectively predict permeability in the reservoir. Finally, the core permeability was compared to the permeability values obtained by the three methods: (i) from the CN, (ii) from the best-EN and (iii) gotten from empirical equation (EE). Figure 8 shows the plot of predicted/calculated permeability versus the target/actual permeability for core, committee network, empirical equation (EE) and the best expert network (Best-EN). Table 4 is a summary of correlation coefficient and the rank for each method. The table shows that the CN has the best correlation with core permeability. Table 4 is a summary of correlation coefficient and the rank for CN, Best-EN and EE.

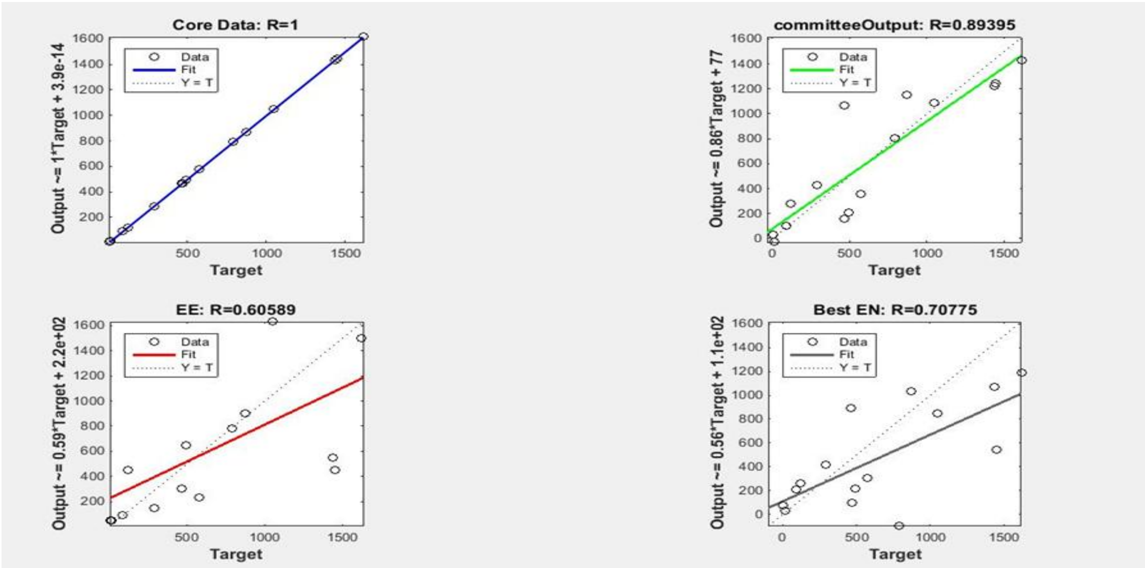

Figure 8: permeability correlation plots for core, committee network, empirical equation (EE) and the best expert network (Best-EN)

Table 4 Summary of correlation coefficient and the rank for CN, Best-EN and EE.

METHOD	Correlation coefficient (R)	RANK (highest to smallest)	**COMMENT**
CN	0.894	3	Best network
Best EN	0.708	2	
EE	0.606	1	

CONCLUSION

In this study, we used neural network toolbox in MATLAB to create two (2) optimal network architectures: CN and Best-EN; which had sufficient capacity to map the statistical relationship between well logs and core permeability. When unseen well-B well logs were supplied as inputs to this networks, they predicted permeability values, which matched acceptably with core data.

The three methods, CN, EN and EE, yielded respective correlation coefficients for permeability as **0.89: 0.71: 0.61**. Clearly, the correlation values for CN and EN gives a better prediction of the core data compared to EE. Also, the CN outperformed the ENs because it leveraged on the collective knowledge and expertise of the each EN.

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