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Application of Optimized Artificial Neural Networks for Predicting Reservoir Permeability

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ABSTRACT

Permeability is one of the most important reservoir properties, which indicates the ability of fluids to flow through the pore spaces of the rock. determining permeability in processes such as predicting real reserve, producing and developing oil reservoirs seems essential. In the oil industry, permeability is usually measured using core analysis, well testing, and empirical correlations. The conventional methods of core analysis and well testing are too time-consuming and expensive. also, there data are not provided for every well. On the other hand, empirical correlations are used for special cases and are not accurate for every situation. Due to time-related and financial limitation, developing a method for measuring petrophysical properties such as: permeability based on well logging data (well logging data are available for almost every well) could be significant. An alternative approach for evaluating permeability is the use of artificial intelligence and machine learning tools. In this study, the method of data mining has been applied to calculate reservoir permeability by applying petrophysical data, at first, the data had been normalized and then horizontal and vertical permeability of an Iranian reservoirs were calculated using geophysical data and the methods of multiple layer perceptron Neural Network, PSO and GA. The comparison of these methods showed that combining MLP with either PSO or GA yields the best results.

Keywords: *Artificial Neural Network, Permeability, Correlation Coefficient, Mean Square Error, Hydrocarbon reservoir*

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1 Introduction

Hydrocarbon reservoirs are among the main sources of energy in the world. the development of these reservoirs is important due to the decline in oil reserves. Among reservoir properties, permeability is more difficult to measure than water saturation and porosity. permeability is usually measured by direct experimental methods of cores and well tests, which are exact but not accurate to describe all the reservoir layering. therefore, the results are limited to a specific rock and layer and are not continuous plots of permeability for reservoir applications [1, 2]. presented a method that can generate continuous plots and serve as a useful alternative [3]. (Since of well logging and petrophysical data availability, these data are used to correlate permeability, however due to needs of core analysis, are limited [4]).

In conventional methods, a statistical correlation between permeability and well logs using different methods of regression (Linear, multiple or single variables, non – linear) have been evaluating. After finding a proper mathematical correlation, the value of permeability has been estimated [5]. Application of linear and even non-linear regression leads to great deviation, since the relations between permeability and independent input variables (such as data acquired in well logs) are mostly non-linear and complicated.

In non-linear regression, the results are highly dependent on mathematical model processed operations and types of input variables [6]. In order to measure permeability presence of a precise, inexpensive, less time – consuming approach such as Artificial Intelligence and machine learning seems essential. Recently, applications in different fields of engineering and sciences shows its potential to estimate petrophysical parameters. Some researchers showed that neural networks could predict permeability by using of geophysics or well loggings [7].

Applying Neural Networks analysis on acquired geological data indicated that sever heterogeneities exist in reservoir such that it cannot be predicted by conventional methods.

Due to this data are categorized as input data (Dolomite, Caliper, Depth, Anhydrite, Shale, Calcite, $\emptyset s$, R_t, S_{gr}) and output data (horizontal and vertical permeability).

2 A review on Artificial Intelligence methods

2.1 *Artificial Neural Networks*

Artificial Neural Networks (ANN's) have been used for over 50 years; however, its main application refers to less two decades ago and it’s growing contemporary. The idea of ANNs is inspired by the structure of the mammalian brain in which millions of neural cells could communicate to solve a problem or store information. Overall, ANN's are novel systems and methods for machine learning, knowledge representation and applying science for predicting output results from complicated systems ANN has usages in different fields of industry, science, medicine, engineering (electronics, transmission, oil and gas), financial affairs, etc [8].

ANN can make a mathematical model from a group of inputs and outputs to give correct results for any inputs. One of the main categories of ANN is included of supervised and unsupervised NN.

In supervised learning, an output is produced from each educated input. while, in unsupervised learning network operates automatically. Most of neural network’s applications in oil and gas industry are based on supervised learning algorithm.

ANNs included some layers: at first there is an input layer in which information can be entered. Secondly, hidden layers exist that can include some neuron (nodes) to communicate between inputs and outputs.

Processing operation in these layers are evaluated using weight correlations and the results are transmitted to third layer (output layer).

Thus, the results are output replies concluding inputs, weights, bias and hidden layer elements. in hidden layer and output layer Sigmoid function is usually used for output calculations.

2.2 *multi-layer perceptron or MLP*

MLPs are kinds of neural networks that have so many applications in modeling and predicting permeability in petroleum industry. in MLP each neuron joins previous neurons, called continues or related networks [9]. neurons can produce different motive functions including sigmoid logarithm, sigmoid tangent and motive function (Figure 2).

2.3 radial basis function or RBF

These networks require more neurons compared to standard network; however, they could be taught rather fast compared to pre-input networks. RBF networks work efficiently with a large number of inputs and RBF networks are a kind of feed-forward network and are very similar to MLP networks [10]. Figure 3 shows a schematic of an RBF network. This network maps N-dimension input pattern using neighborhood layer to nodes output pattern of Z-dimension.

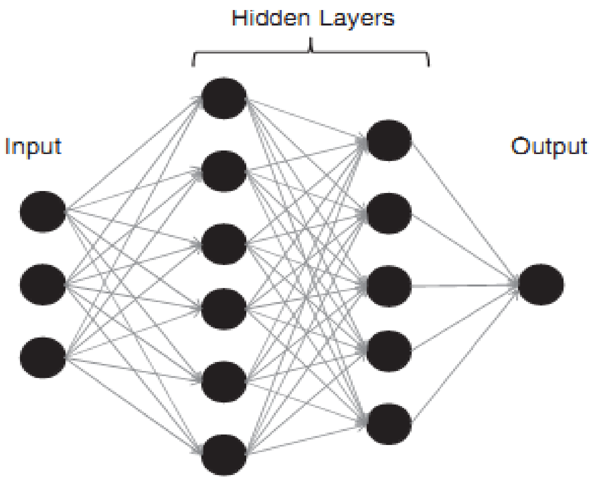


Figure 1. An MLP ANN with an input layer, two hidden layers and an output layer [1]

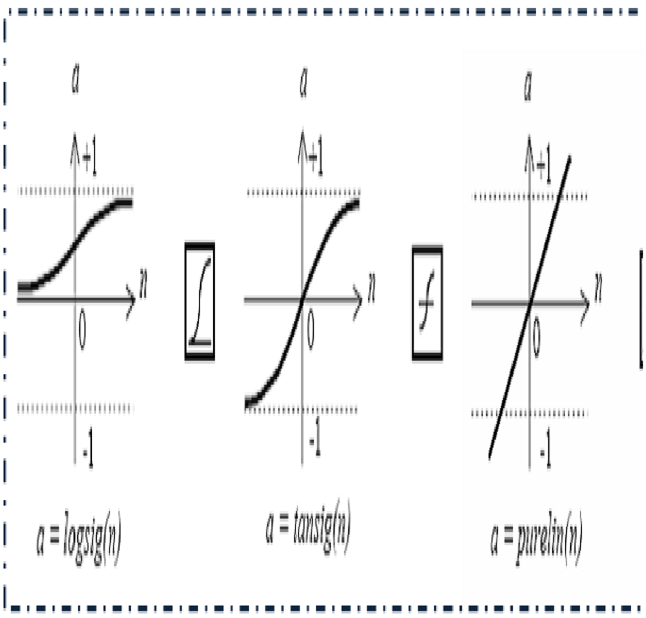


Figure 2. Common stimulus functions in MLP [11]

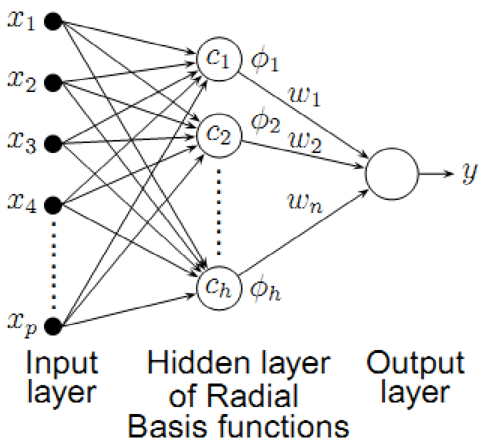


Figure 3. View of the RBF network [10]

Inputs of RBF Neurons are different compared to other neurons. in radial neurons inputs of transmission function is equal to the distance between weights and inputs are multiplied by bias. input layer sends the magnitude of input to each hidden layer.

Each node in hidden layer is distinguished by a transmission function (f) which transmit input signals.

2.4 genetic Algorithm

GA, is a method of learning based on biological evolution. this method exposes a group of possible solution. each is evaluated using a proportionality function. then, some solution can produce new solution make the original solution. therefore, the domain of solution can be evolved in order to get the interested solution [12, 13].

2.5 particle swarm optimization

PSO algorithm is an optimized, super-discovered and is originated from bird's flight. the described algorithm, is one of the most successful algorithms in discretized and continues optimization. in this algorithm, each answer rely is modeled that has magnitude [14]. this method converges quickly since it is according to population and no reply combination could happen in.

Overall, PSO algorithm works according to particles movement and mind and applies social communication for optimization problems.

Finally, the efficiency of each network is evaluated. we used method of ANN (RBF, MLP), optimized MLP (GA, PSO). Two following indices are used as criteria of choosing best method.

1. Correlation coefficient (R): is a dimensionless coefficient, ranges between 0 and 1. its best value approaches to unity.
2. Mean Square Error (MSE): indicates the magnitude of error in ANN the interested value of MSE approaches zero.

$$\varepsilon(n) = MSE = \frac{\sum_{n=1}^{n}(E_n - R_n)^2}{n} \quad (1)$$

Where R_n is observed values, E_n is estimated value and n is amount of data for learning networks.

For a better fitness, weights and bias should be changed to reduce errors. Change in weights and bias can be performed based on optimized algorithms.

3 Case Study

The current study is carried out based on the data from one of the Iranian south fields. The data shows that the related reservoir is layered and heterogeneous. conventional methods are not sufficient for petrophysical estimation. out of all drilled wells, three were selected for evaluation. these wells intersect the reservoir and are fairly far from each other, core analysis data are provided for them, too.

The following data are used as inputs of neural network:

- Spectral Gamma Ray (SGR) For lithology evaluation including shale regions.

- Electrical Resistivity (R_t) for determining water saturation.

-Water saturation data for indicating permeable zones.

-Effective or secondary porosity for the finding relation between porosity and permeability. Shale, Dolomite, Anhydrite and Calcite are types of lithology. Caliper's data are used for showing well diameter, Depth logs are used for determining the effect of over burden pressure. we want to evaluate vertical and horizontal permeability.

3.1 Data analysis and methods of ANN creation

There were numerous petrophysical parameters in the prescribed; however, the most effecting ones were considered. we organize data as input data (Depth, Anhydrite, Shale, Calcite, Dolomite, Caliper, $\emptyset_S$, $\emptyset_E$, S_w, R_t, S_{gr}) and output data (vertical and horizontal permeability). The application was written in separated files for process of network learning.

The steps of ANN creation (MLP and RBF) are given below:

A) The effect of input parameters is the first step to create an artificial intelligence method. introduction of numerous high numbers of inputs, makes the site of neural network larger and the speed of learning education retard.

B) Before entering data in ANN's, a pre-process has been implemented to investigate whether or not any parameter receives the same attention and works recognition speed between different numbers distracts, data have been normalized.

C) From all available data, 70% were used for training, 15% for validation, and 15% were used for testing in MLP method.

For RBF 70% and 30% were used for training and testing, respectively.

D) In order to create network's structure, number of hidden layers existed neuron in each layer should be determined. number of input and output neurons is the same number of input and output parameters.

E) In order to prevent pre-processing defects, data of learning were used in all methods number of cycles in each network were unknown and as soon as errors in data of learning began to increase, learning algorithm was stopped.

F) After learning a set of data has been presented to MLP network and the produced results compared with real data (vertical and horizontal permeability), the match of these data was used as criterion of extension.

Validation of network was evaluated during education (learning) and the moment that error on validation data starts increasing, educating the network stops. (if MSE reaches the predicted value it will stop too).

G) Examination: this stop is for post – propagating networks. In these networks, the error is controlled after ending of each cycle. we used Neuron solution, WEKA, MATLAB, ZOB, Excel for our processing.

3.2 Modeling

3.2.1 MLP Method

The method of MLP was used for prediction due to its (feed-forward) application and its high ability [9]. That's why this method was used for vertical and horizontal permeability prediction. eleven inputs (for each permeability) have been entered in prescribed input layer network. There were two hidden layers for getting data and one output (again for each permeability) for entering result. we tested different hidden layers with different neurons and found out that the best method is two-layer (Layer R, less MSE).

The method of sigmoid tangent (Tansig) for hidden layer inputs and linear (purelin) for hidden layer to output were used. Back propagation and type of (Marguardt–levenberg) was used for network learning with average to small size due to fair convergence.

Form 248 data, 174,37,37 of them were used in training, validation and testing. Average square error for methods of single-layer and three-layer perceptron were greater than two- layer perceptron (Correlation index were smaller), and thus, the result of two-layer only is brought here.

The best value of R, MSE are obtained from MLP (learning network from type of Marguardt–levenberg), and optimized MLP by methods of PSO and GA (Table 1,2). The best value of prementioned parameters for normalized MLP (learning network: Marguardt–levenberg) that is optimized by GA are in Table 3,4. a flowchart of GA and PSO methods are in Figure 4, 5 respectively.

Table 1. Comparison of the best results for R and MSE using MLP optimized by GA and PSO for horizontal permeability

Parameter	MLP	MLP optimized with GA	MLP optimized with PSO
R (Total data)	0.97002	0.99281	**0.99449**
MSE (Total data)	0.0017569	0.00042422	**0.00032517**
R (Learning data)	0.97881	0.99185	**0.99628**
MSE (Learning data)	0.0011322	0.00045699	**0.00020979**
R (Validation data)	0.97501	0.99248	**0.98389**
MSE (Validation data)	0.0015745	0.0005864	**0.00097193**
R (Testing data)	0.94171	0.99808	**0.99719**
MSE (Testing data)	0.0048768	0.000342	**0.000221**

Table 2. Comparison of the best results for R and MSE using MLP optimized by GA and PSO for vertical permeability

Parameter	MLP	MLP optimized with GA	MLP optimized with PSO
R (Total data)	0.94537	0.9976	**0.98552**
MSE (Total data)	0.0015893	0.000071422	**0.00085198**
R (Learning data)	0.95251	0.99828	**0.98672**
MSE (Learning data)	0.0011938	0.000044505	**0.00072373**
R (Validation data)	0.94905	0.98832	**0.98445**
MSE (Validation data)	0.00044481	0.00016801	**0.0015823**
R (Testing data)	0.93273	0.99843	**0.98162**
MSE (Testing data)	0.0045932	0.000096852	**0.00072477**

Table 3. The results of employing different designs, two-layer perceptron normalized and optimized using GA (Education Network type Marguardt–levenberg) to predict the horizontal permeability (for the 15% test), the best result (highest R, lowest MSE) has been bolded.

No. of Networks	No. of neurons in two-layer config.	R	MSE
1	[2 2]	0.9318	**0.003510**
2	[3 3]	0.97622	**0.0017312**
3	[4 3]	0.99808	**0.000342**
4	[7 9]	0.81939	**0.0073574**
5	[10 10]	0.9289	**0.003615**
6	[14 13]	0.84072	**0.50869**
7	[15 15]	0.903	**0.0078198**

Table 4. The results of employing different designs, two-layer perceptron normalized and optimized using GA (Education Network type Marguardt–levenberg) to predict the vertical permeability (for the 15% test), the best result (highest R, lowest MSE) has been bolded.

No. of Networks	No. of neurons in two-layer config.	R	MSE
1	[2 2]	0.94678	**0.0015503**
2	[3 3]	0.99843	**0.00096852**
3	[4 3]	0.97037	**0.00098235**
4	[7 9]	0.93789	**0.0012449**
5	[10 10]	0.9581	**0.004963**
6	[14 13]	0.85665	**0.002528**
7	[15 15]	0.95427	**0.009444**
8	[15 15]	0.95427	**0.009444**

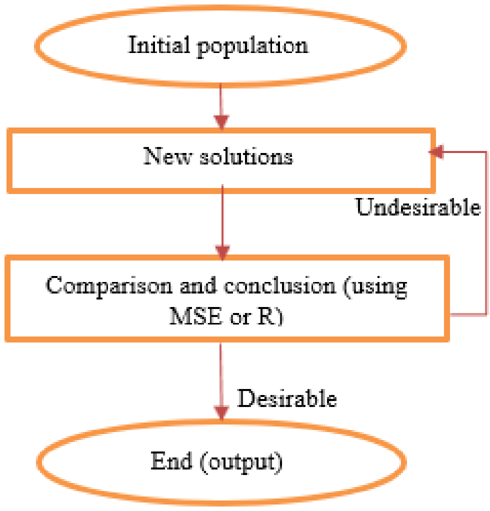


Figure 4. GA flowchart

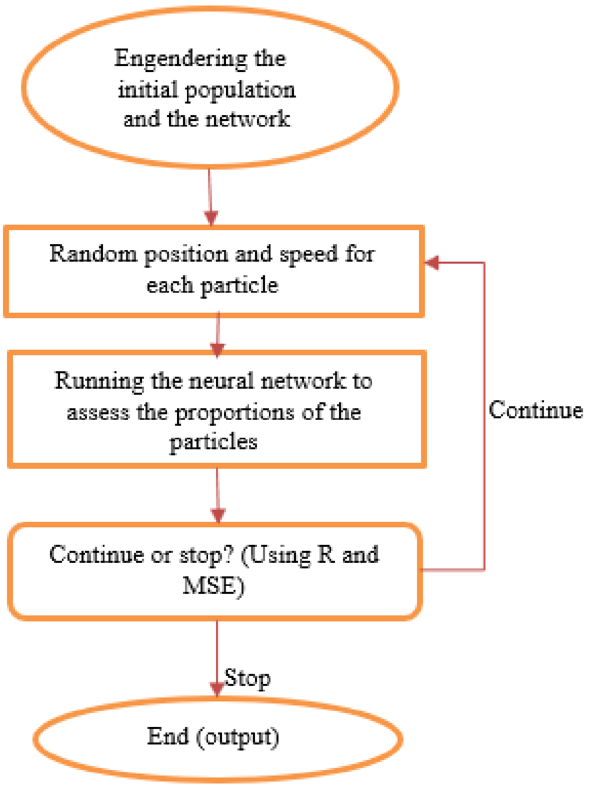


Figure 5. PSO flowchart

Comparison of examination part for real and predicted permeability with normalized data (MLP optimized GA, PSO) are given in Figure 6 and 7.

Also, Comparison of the best R (largest) and MSE (smallest) for horizontal and vertical permeability and predicted value using normalized MLP (learning network: Marguardt–levenberg) are presented in Figure 8.

Normalized MLP Network Efficiency plot at its best condition is given in Figure 9.

The effect of input parameters on horizontal and vertical permeability's are indicated in Figure 10.

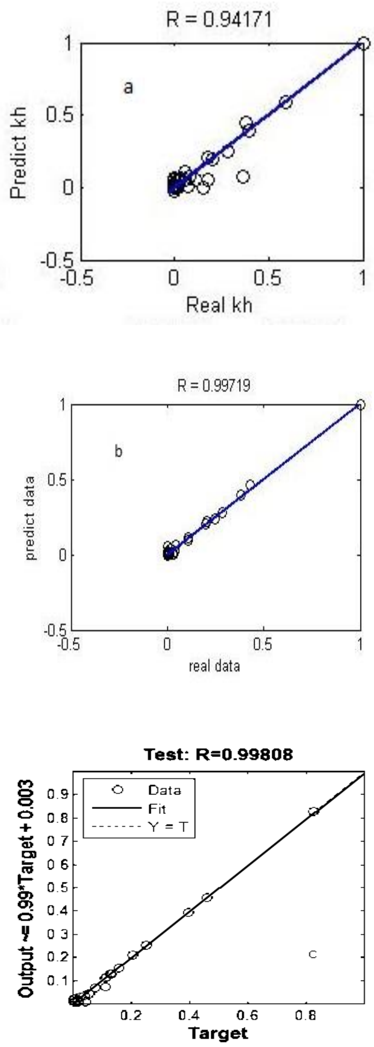
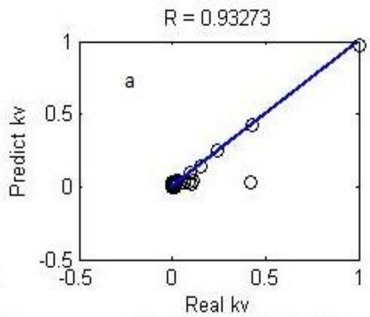


Figure 6. Comparison between the actual (horizontal axis) and predicted permeability (vertical axis) with Normalized data for horizontal permeability methods MLP (a), MLP combined with PSO (b) and MLP combined with GA (c)



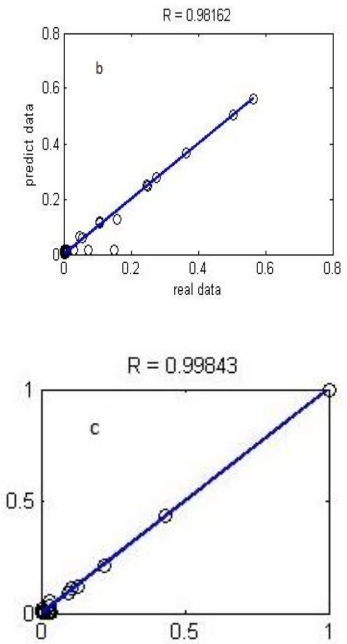


Figure 7. Comparison between the actual permeability correlation coefficient (horizontal axis) and predicted permeability (vertical axis) with Normalized data for vertical permeability methods MLP (a), MLP combined with PSO (b) and MLP combined with GA (c)

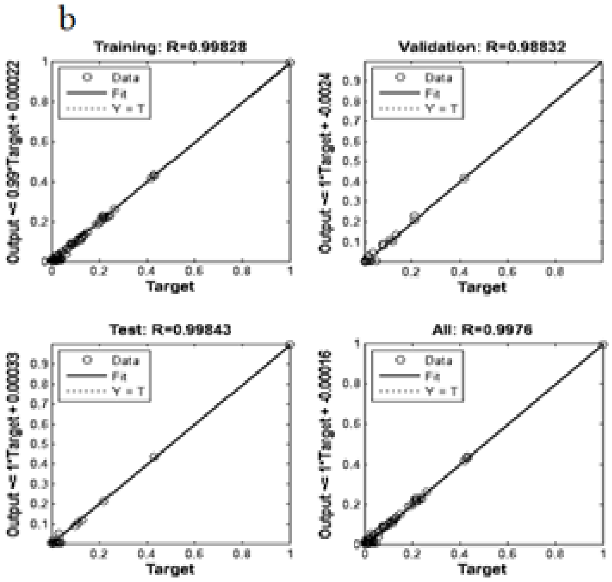


Figure 8. Comparison of the normalized correlation coefficient of the real permeability (horizontal axis) and predicted permeability and normalized (vertical axis) using MLP (optimized using GA) for horizontal Permeability (a) and vertical permeability (b) (where the network training Type Marguardt–levenberg).

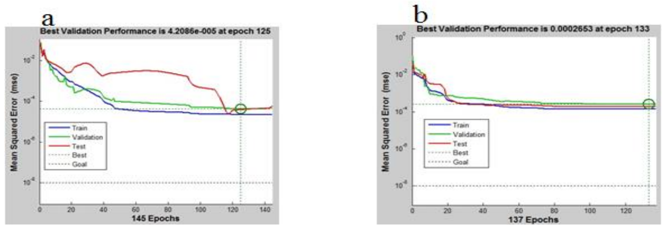


Figure 9. Plot normalized MLP network performance in the horizontal permeability (a) and vertical permeability (b)

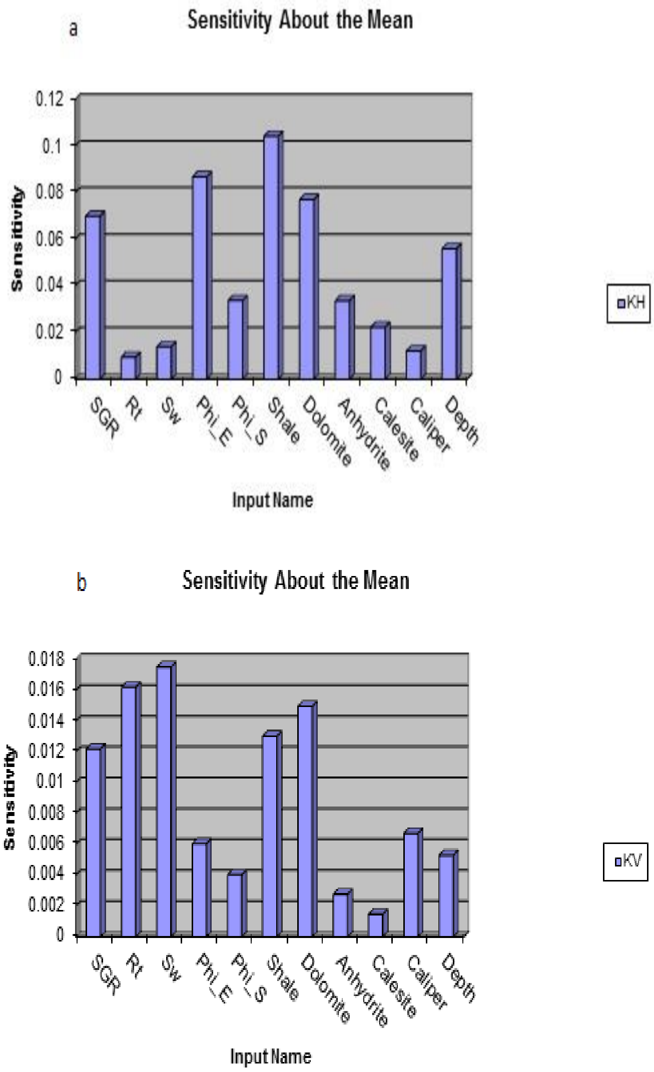


Figure 10. The effect of the input parameters used in the neural network training to estimate horizontal permeability (a) and vertical permeability (b)

3.2.2 RBF Method

As it's mentioned before these networks works better when lots of input parameters are provided.

In this method, the validation part is omitted. RBF uses a radial structure that has a better consistency when number of inputs increases.

We used the same number of 248 data (174 training and 74 for testing vertical and horizontal permeability's (in both RBF and GPR). the best magnitudes (normalized) R, MSE from RBF (Marguardt–levenberg) and optimized RBF with different methods for permeability's are tabled in Tables 5 and 6.

Comparison of the best R (largest), MSE (smallest) for horizontal and vertical permeability and predicted value using normalized MLP (learning network: Marguardt–levenberg) for test data are presented in Figure 11.

Table 5. Comparison between the best values of R and MSE are normalized horizontal permeability obtained from RBF (Education Network type Marguardt–levenberg)

Parameter	RBF
R (Total data)	**0.99366**
MSE (Total data)	**0.00037785**
R (Learning data)	**1.00**
MSE (Learning data)	**6.6118E-25**
R (Testing data)	**0.98456**
MSE (Testing data)	**0.0012663**

Table 6. Comparison between the best values of R and MSE are normalized vertical permeability obtained from RBF (Education Network type Marguardt–levenberg)

Parameter	RBF
R (Total data)	**0.99247**
MSE (Total data)	**0.00023136**
R (Learning data)	**1.00**
MSE (Learning data)	**2.96866E-25**
R (Testing data)	**0.98244**
MSE (Testing data)	**0.00077538**

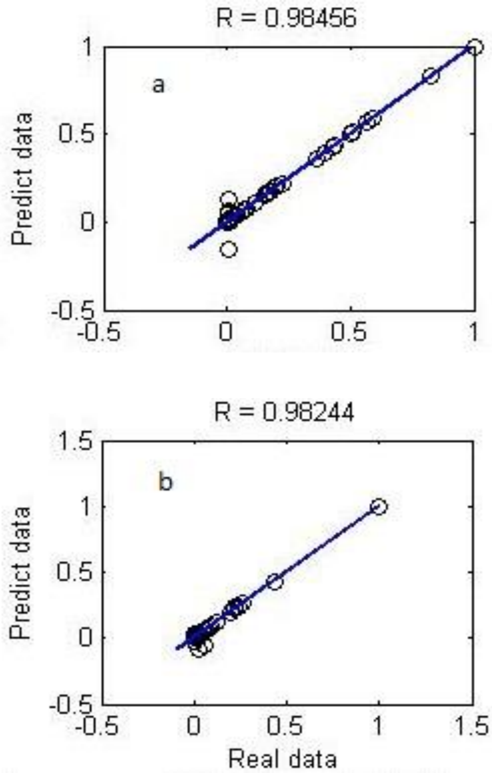


Figure 11. Comparison between actual permeability correlation coefficient (horizontal axis) and predicted permeability (vertical axis) Normalized RBF method for horizontal permeability (a) and vertical permeability (b) for test data

The results show that methods of MLP (optimized with PSO and GA) and RBF have acceptable results for reservoir. however, in method RBF validation part has been omitted and it's not reliable as much as the MLP.

4 Results

Despite Gaussian Process's Regression model, neural network methods don't require complicated mathematical models. the most important issue of these methods is choosing suitable learning algorithm.

It is not necessary to know the detailed rock or in-situ fluid properties when using neural network methods. you have to choose inputs in a way that the effect of output parameters (vertical and horizontal permeability) had been considered.

In carbonated formations, vertical permeability differs from horizontal permeability.

Thus, both permeability's has to be used. Anisotropic permeability is a function sedimentary history, diagnosis, shale amount and formation compressibility overall.

5 Nomenclature

R	Correlation Coefficient
MSE	Mean Square Error
ANN	Artificial Neural Networks
GA	Genetic Algorithm
PSO	Particle Swarm Optimization
K	Permeability, md
$\emptyset s$	Second Porosity
$\emptyset e$	Effective Porosity
Sgr	Spectral Gamma Ray
Rw	Water Resistivity
MLP	Multi-Layer Perceptron

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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