Petroleum and Coal

Article Open Access

Improved Estimation of Permeability of naturally fractured carbonate Oil Reservoirs Using Wavenet Approach

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Received June 18, 2017; Accepted September 30, 2017

Abstract

One of the most important parameters which is regarded in petroleum industry is permeability that its accurate knowledge allows petroleum engineers to have adequate tools to evaluate and minimize the risk and uncertainty in the exploration of oil and gas reservoirs. Different direct and indirect methods are used to measure this parameter most of which (e.g. core analysis) are very time-consuming and cost consuming. Hence, applying an efficient method that can model this important parameter has the highest importance. Most of the researches show that the capability (i.e. classification, optimization and data mining) of an Artificial Neural Network (ANN) is suitable for imperfections found in petroleum engineering problems considering its successful application. In this study, we have used a Wavenet Neural Network (WNN) model, which was constructed by combining neural network and wavelet theory to improve estimation of permeability. To achieve this goal, we have also developed MLP and RBF networks and then compared the results of the latter two networks with the results of WNN model to select the best estimator between them.

Keywords: Permeability; Wavelet; Neural Network; MLP; RBF; Model.

1. Introduction

Permeability prediction is one of the main challenges in reservoir engineering. On the other hand, suggesting engineering methods to solve reservoir modeling and managements is impossible without the knowledge of the actual permeability values. The reservoir rock permeability cannot be measured directly with exception of using core plugs as direct measurement. However, direct measuring methods are expensive and time-consuming. In recent years, intelligent techniques such as Artificial Neural Networks (ANNs) have been increasingly applied to estimate reservoir properties using well log data. Moreover, previous investigations have indicated that neural networks can estimate formation permeability even in highly heterogeneous reservoirs using geophysical well log data with good accuracy [1].

Intelligent methods generally utilize raw well log data to estimate permeability, and core plug measurements are used to validate the estimations. Thus, intelligent technique can be utilized as a powerful tool for reservoir properties estimation from well logs in oil and natural gas development projects .Neural network has accurate results but complex structures need more improvement in network [2].

Wavenet is a feed forward and new class of network that combines the classic sigmoid neural networks (NNs) and the wavelet analysis (WA). To detect relation between variables in the main signal, WNN finds family of wavelets in estimation space. WNN has two properties: transfer wavelet and a global estimator. At the same time, wavelets functions in addition to perpendicular properties have good local properties. These properties cause a quick homogeneity than normal neural network. These networks can estimate a function with every accuracy by using multi resolution technique [3].

The main objectives of the present study are:

- To develop a MLP-NN model to estimate of permeability from well log data;
- To develop a RBF-NN model to estimate of permeability from well log data;
- To develop a Wavenet-NN model to estimate of permeability from well log data;
- To validate models with core data and compare the abovementioned approaches;

In this study, a case study of Asmari reservoir located at Ahwaz oil field of Iran is presented. To estimate the permeability of the reservoir, the MLP, RBF and Wavenet methods are used. We designed a Wavenet model to improve estimation of permeability of reservoir. We compare the results of Wavenet, RBF and MLP models to identify the best model to estimate permeability to achieve this goal.

A summary of literature review is shown in Table 1.

Table 1. Summary of literature review.

Author	Year	Methodology	Objective	Results
R. Soto B [6]	1997	Neural network (Back propagation algorithm)	Estimate K and Ø	Create accuracy and easy to apply model with satisfactory estimations
Mohsen Saemi [7]	2007	Neural network(genetic algorithm)	Estimation permeability	GA was able to sufficiently estimate the permeability with high correlation coefficient
Sadegh Karimpouli [8]	2010	Supervised committee machine neural network (SCMNN)	Estimate permeability	The high power and efficiency of SCMNN to compare with simple network
Irani and Nasimi [9]	2011	Genetic algorithm	Improve the reliability and predictability of artificial neural network	Better results of proposed network than simple network
Tahmasebi and Hezarkhani [10]	2011	Modular neural network (MNN)	Estimate permeability	Very low computational time, increase R^2 and the ability to encounter with complex problems
Kaydani and Mohebbi [1]	2012	Combining cuckoo, particle swarm (PSO) and imperialist competitive algorithms (ICA) with Levenberg–Marquardt (LM) neural network algorithm.	Estimate permeability	The COA–LM neural model produces a high accuracy than without the optimization method
El-Sebakhy [2]	2012	functional networks	Forecast permeability	Accurate, reliable, and outperforms most of the existing predictive modeling approaches
Anifowose [11]	2012	Adaptive Neuro-Fuzzy Inference System (ANFIS) and two innovative hybrid models	Compare three versions of Adaptive Neuro-Fuzzy Inference System (ANFIS) hybrid model and two innovative hybrid models in the prediction of oil and gas reservoir properties	FN-SVM hybrid model had better performance, the highest R^2, lowest MSE, but taking longer time to execute than the 3 ANFIS algorithms
Maslennikova [12]	2013	Hybrid neural network model consisting of several computational and one clustering neural networks	Predict permeability	Increases permeability modelling accuracy

Author	Year	Methodology	Objective	Results
Viveros and Parra [13]	2014	Artificial Neural Network (ANN) models	estimate (k), (φ) and intrinsic attenuation (1/Q)	Found nonlinear relations that were not visible to linear regression
Shokooh Saljooghi and Hezarkhani [5]	2014	Wavelet network (wavenet)	Estimate porosity	Increase R^2 and decrease MSE than MLP
Shokooh Saljooghi [14]	2015	Wavelet network (wavenet)	Estimate permeability	Substituting different wavelet functions as feed forward neural network transfer functions can enhance the network performance and efficiency

2. Artificial neural networks

One of the types of intelligence methods is artificial neural networks (ANNs). This method is inspired by biological neural networks. ANNs are created with neurons that are arranged to create input, hidden and output layers. Neurons are the large number of simple calculating parameters. They further include interconnections between the nodes of successive layers through the so-called weights. Weight modifies the signal carried from one node to the other and improves the influence of the specific connection. Each neuron in a layer receives weighted inputs from a previous layer and transmits its output to the neuron in the next layer then plus it with bias. The internal weights of the network are adjusted in the course of an iterative process termed training and the algorithm used for this purpose so-called training algorithm. A back-propagation neural network 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 back-propagation (BP) algorithm is the most common form of learning, utilized today in artificial neural networks. There exist many network architectures but Multilayer Perception is one of the most popular among them. The number of nodes in the feed forward neural network input layer is equal to the number of inputs in the process, whereas the number of output nodes is equal to the number process output.

Basically, the back-propagation training procedure is intended to obtain an optimal set of the network weight, which minimizes an error function. The commonly employed error function is the mean squared error (MSE) as defined by [4]:

MSE= ½ ∑ (yiobs – yiout) for i=1,…, n. (1)

where y_i^{obs} and y_i^{out} are respectively the observed and estimated values.

2.1. Multi-layer perceptron (MLP)

MLP with back propagation (BP) algorithm is the most popular artificial neural network, as mentioned earlier. MLP is a network with an input layer, an output layer and one or more hidden layers that consist of neurons.

For assignment number of hidden layers and neurons, we can use trial and error procedure. Thus, we select the number of neurons with highest regression (R) and lowest mean square error (MSE).

The summation of weighted input signal is calculated by using the following equation:

ynet = ∑ xi wi + wb for i= 1,…,n (2)

where *ynet* is the summation of weighted input, *xi* is the neuron input, *wi* is the weight associated with each neuron input, *wb* is the bias, and *n* is the number of examples (instants).

The results from equation 2 can be transformed by a non-linear activation function given by:

yout = f(net) = (1+ e-y(net))-1 (3)

where *yout* is the response of neural network system and *f* (net) is the non-linear activation function.

Training steps in artificial neural network include:

1- Feed samples with input vectors through constructed network

2- Calculate the error of output layer
3- Minimize error by alignment the weight of network

We use BP learning algorithm, a supervised learning to construct MLP network. Standard BP is a gradient descent algorithm in which the network weights are moved along the negative of the gradient of the performance function. In BP algorithm, the descent is based upon the gradient ΔE for the total training set according to the following equation:

$\Delta w_{ij} = -\mu^* \delta E/\delta w_{ij} + \alpha^* + \delta w_{ij}(n-1)$ (4)

where μ^* and α^* are the learning and momentum parameters. The momentum term calculates the effect of past weight changes on the current direction of movement in the weight space.

We can select these parameters nicely, if we have a successful training and high speed in network learning. MLP is a global network that its construction process is very time consuming because to calculate number of neurons, we should use trial and error [5].

In this study, the training algorithm of the model is the back propagation. In order to speed up the training, the Levenberg-Marquart algorithm is used which has a great effect on speeding up the training. The number of hidden layers is one which is the most common. The neurons into the input layer are the well logs and the output layer consists of one neuron which is the core permeability that should be estimated. A tangent sigmoid activation function is used for the hidden and output layers.

2.2. Radial basis function network

Radial basis function (RBF) network is similar to the multilayer perceptron model, the basic RBF model provides a nonlinear transformation of a pattern x ϵ Rp to g(x) ϵ R or g(x) ϵ {1, . . . , c}, that is,

$gj(x) = \sum wji\, Ø\, ((\|x-\mu i\|)/h) + bj \quad j = 1,\ldots,c \ (\text{for } i = 1,\ldots,m)$ (5)

where *m* is a constant representing the number of basis functions, *wji* is a weight, *bj* is a bias, Ø (0) is a radial symmetric basis function, μi ϵ Rp is called a center vector, and h ϵ R is a smoothing parameter.

We note that RBF based upon equation has almost the same mathematical form as that of MLP networks, the key difference being that the logistic function is replaced by a radial basis function, which is often taken to be the Gaussian function $Ø(z) = e\text{-}z^2$, where $z = h\text{-}1 \|x\text{-}\mu\|$.

The RBF adopts least-squared errors optimization criterion to estimate the weights *wji* within the selected architecture of the RBF networks. Unlike the multilayer perceptron model, where all parameters are optimized at the same time, in the radial basis function networks model, both center vectors and weights are found in two separate steps. In the first step, the center vectors are found using some existing pattern recognition techniques (such as k-means clustering or the Gaussian mixture). In the second step, a set of linear equations is solved to find the optimal weights and biases [2].

3. Wavelet Analysis

Wavelet theory has many applications in numerical methods and signal processing. We can use wavelet transfer for the function approximation problem. Wavelet is a little wave that has minimum sway and the term "wavelet", as it implies, means a little wave. This little wave must have at least a minimum oscillation and a fast decay to zero, in both the positive and negative directions, of its amplitude. This property is analogous to an admissibility condition of a function that is required for the wavelet transform. For a function ψ (0), defined over the real axis (-∞, +∞), to be classed as a wavelet, it must satisfy the following three properties [15]:

(1) The integral of ψ (0) is zero:

$\int \psi(u)\, du = 0 \quad (-\infty, +\infty)$ (6)

(2) The integral of the square of ψ (0) is unity:

$\int \psi^2(u) = 1 \quad (-\infty, +\infty)$ (7)

(3) Admissibility Condition:

$C_\psi = \int (|\psi(f)|^2 / f)\, df \quad (0, +\infty)$ (8)

Wavelet transforms have emerged as a means of representing a function in a manner that readily reveals properties of the function in localized regions of the joint time –frequency space. The primary advantages that wavelets have to offer over other activation functions are:

- They guarantee the universal approximation property.
- Initial values for the learning may be obtained from the continuous or discrete wavelet coefficients and thus enable faster convergence.
- If orthogonal wavelets are used, then adding or removing nodes from the network does not affect those weights which have already been trained. This is true since components at different scales lie in orthogonal subspaces.

These features lead to fast, localized, and hierarchical learning. A wavelet $\psi_j(x)$ is derived from its mother wavelet by the following relation:

$\psi_j(x) = \psi((x-t_j)/d_j) = \psi(z_j)$ (9)

where the translation factor t_j and the dilation factor d_j are, respectively, real numbers in R and R^*.

The family of functions generated by ψ can be described as the following:

$\Omega_c = (1/\sqrt{d_j})\ \psi((x-t_j)/d_j) \quad t_j \in R \quad \text{and} \quad d_j \in R^*$ (10)

A family Ω_c is said to be a frame of $L^2(R)$ if there exists two constants C>0 and $C < \infty$ such that for any square integrable function f, the following inequalities hold:

$C\| f \|^2 < \sum \psi_j, f < C \|f\|^2$ (11)

where f denotes the norm of function f and <f, g> the inner product of functions f and g.

Families of wavelet frames of $L^2(R)$ are universal approximators. In the framework of the discrete wavelet transform, a family of wavelets can be defined as:

$\Omega_d = \{\alpha^{2/m}\ \psi(\alpha^m x - n\beta), (m, n) \in z^2\}$ (12)

where α and β are constants that fully determine, together with the mother wavelet ψ, the family Ω_d. Actually, relation 12 can be considered as a special case of relation 10, where [14]:

$m_j = n\alpha^{-m}\beta \quad \text{and} \quad d_j = \alpha^{-m}$ (13)

4. Wavelet neural network and its structure

Wavelet neural networks combine the theory of wavelets and neural networks into one. A wavelet neural network generally consists of a feed-forward neural network, with one hidden layer, whose activation functions are drawn from an orthonormal wavelet family. The structure of a wavelet neural network is very similar to that of a (1+ 1/2) layer neural network. That is, a feed-forward neural network, taking one or more inputs, with one hidden layer and whose output layer consists of one or more linear combiners. The hidden layer consists of neurons, whose activation functions are drawn from a wavelet basis. These wavelet neurons are usually referred to as wavelons.

Wavelet frames are constructed from mother wavelet which is a prototype for generating the other window functions. A wavelet $\psi_j(x)$ is derived from its $\psi(z_{jk})$ mother wavelet.

It is shown in this equation:

$\varnothing_j(x) = \Pi\ \varnothing(z_{jk}) \quad z_{jk} = (x-t_{jk})/d_{jk} \quad \text{for } k= 1,\ldots,Ni.$ (14)

N_i, is the number of inputs. The network output y is computed using this equation:

$y= \sum c_i\ \varnothing_j(x) + \sum a_k x_k \quad \text{for } j=1,\ldots,N_w \text{ and } k=1,\ldots,N_i$ (15)

The training is based upon the minimization so that quadratic cost function has been used as shown in equation 16:

$J(\theta) = 1/2\ \sum(y_p - y)^2$ (16)

In equation 16, y is the network output and y_p is the process output which information flowing out of the system. The minimization is performed by iterative gradient basic methods. The partial derivative of the cost function with θ is computed using this equation [14]:

$(\delta j/\delta\theta) = -\sum e\ (\delta y/\delta\theta) \quad \text{and} \quad \theta = \{t_{jk}, d_{jk}, c_j, a_k\}$ (17)

At present, there are two different kinds of WNN structures. One is with fixed wavelet bases, where the dilation and translation parameters are fixed and called wavenet, and only the output layer weights are adjustable. Another type is the variable wavelet bases, where the dilation parameters, translation parameters and the output layer weights are adjustable which is called wavelet network [16]. In this study, we used first structure to estimate permeability.

There are two main approaches to creating wavenet:

- In the first, the wavelet and the neural network processing are performed separately. At first, the input signal is decomposed using some wavelet basis by the neurons in the hidden layer. The wavelet coefficients are then output to one or more summers whose input weights are modified in accordance with some learning algorithm.
- The second type combines the two theories. In this case, at first we define a wavelet transfer function (TF) and then we use this TF in neural net [17].

In this study for designing wavenet, at first we process data with wavelet basis and then we import data to ANN to estimate permeability. We use Morlet mother wavelet for transfer function, because in previous works this wavelet has been reported as the best estimator.

5. Data bank

The data set for this study was obtained from 18 wells of Asmari reservoir at Ahwaz oil field in Iran. This field is located in south west of Iran, Khozestan province. The Asmari is well-known as a typical naturally fractured carbonate oil reservoir.

We used different well log data that are related to permeability and existed in each 18 wells. This raw data were processed and so more suitable data were produced. We selected the following parameters: True formation conductivity log (Cond-T) and Water saturation (Sw) to show permeable regions, Gamma ray log (GR) to indicate shale region, Neutron log (NPHI), bulk density log (RHOB), Effective porosity log (PHIE) and sonic travel time log (DT) because of direct relation porosity with permeability, Caliper log and Shale volume to the obvious effect of lithology for reservoir's attributes prediction. The main statistical descriptions of the used data are summarized in Table 2.

Table 2. Statistical descriptions of the used data

Parameter	CALIP	Cond_T	DT	GR	NPHI	PHIE	RHOB	SW	V_SHALL
Mean	6.3912	0.3871	70.0145	50.611	0.17907	0.128976	2.4665	0.5586	0.149079
Median	5.9915	0.1503	66.0083	47.991	0.17754	0.125336	2.503	0.5429	0.117273
Mode	5.9346	0.01	87.5322	27.263	0.10388	0.000002	2.6336	1	0.000006
Std.Dev.	0.87304	0.695	12.8004	26.322	0.07223	0.079061	0.1843	0.3555	0.145475
Kurtois	1.38592	15.109	-1.0248	0.6565	3.67797	-1.00761	-0.8672	-1.423	3.972235
Skewness	1.8001	3.552	0.50653	0.7501	1.07377	0.099147	-0.0234	-0.051	1.667577
Minimum	5.8521	0.0005	49.4433	3.9732	0.01594	0.000001	1.9895	0	0.000006
maximum	8.5814	7.082	102.229	168.43	0.58435	0.322221	3.024	1	0.865474

Table 3 shows correlation between inputs and target, before and after data preprocessing. Before preprocessing of data, results showed that correlation is low. Thus, after removing outliers, results showed that correlation between inputs and target is increased.

Table 3. Correlation between inputs and target

	Caliper	Cond	DT	GR	NPHI	PHIE	RHOB	Sw	V-shale
Before	0.2021	0.2247	0.3724	-0.283	0.0823	0.2569	-0.356	-0.099	0.044
After	0.2588	0.2694	0.4642	-0.354	0.0937	0.3547	-0.460	-0.158	-0.008

6. Methodology

6.1. Training network

Initial results of network validation based upon random selection of input data showed poor and unacceptable results. Since the network is used for estimation, it is essential to divide data into training, validation and test subsets.

The best method that has been done successfully on several projects is sorting of the data based upon the output variable and divide them into three subsets such that cover the space distribution of the output variable completely. In this study, for MLP and WNN networks, 70% of data (500 data) were selected for training stage, 15% (107 data) were selected for testing and 15% for validation stage.

6.2. MLP structure

For design of this model, we used neural net fitting toolbox. We imported two data sets, input (well log data) and output (core permeability). Then, we divided data and we used Levenberg-Marquardt for training algorithm.

Mean Square Error (MSE) and Correlation Coefficient (R) are the main factors for selecting the best number of hidden neurons and other parameters of network configuration in this study. We should compare the MSE and R values of networks with different numbers of hidden layer and networks. We selected the best model with minimum value of MSE and R value close to unity.

6.3. RBF structure

In this model, we divided data into training (70% data) and test (30% data) data. We used self-learning method by MATLAB software for determination of hidden layer neuron and spread parameter (б). The activation function in hidden layer was radial basis function (newrb) and for input and output layer was linear transfer function (purlin).

The network optimization consist of selection of proper values for spread parameter and hidden layer neurons number according to minimum value of MSE and maximum value of R (close to unity) was obtained.

6.4. Wavenet structure

For designing this model, at first we decomposed input data with MORLET wavelet, that in previous works, this wavelet had the best results for function estimation, then an ANN model was constructed and the output data was used for estimation. In this network, 70% of data were selected for training stage, 15% were selected for testing and 15% for validation stage. We used Levenberg-Marquardt algorithm for training. A workflow of study is shown in Figure1.

7. Results and discussion

7.1. Factor analysis

Factor Analysis and PCA methods have similar behavior and their results can be interpreted simultaneously. Multivariate data often includes a large number of measured variables and sometimes those variables overlap, in a sense that group of them might be dependent. In factor analysis, it is tried to identify the factors that have similar source of variability or correlate together by decomposing variability in the multivariate space.

In order to show the essential number of principal components for justifying the variation of data, the Principal Component Analysis (PCA) is done. The results are shown in Table 4 and the Scree Plot is shown in Figure 2.

According to the latter table and figure, the first three principal components include above 80% of variations in 9 input variables for PCA. Only components with Eigenvalue greater than unity are selected as significant components. Thus, with a multivariable linear transformation, the dimensions of input variable are reduced.

The factor loading coefficients is shown in Figure 3.

According to values reported in Table 5, it is obvious that DT, NPHI and PHIE have the most factor loading with positive sign in Factor-1 and it shows the effect of porosity on these variables. Also, Factor-1 RHOB has one of the most factor loading, but with negative sign that shows inverse relationship with mentioned variables. In Factor-2 COND and Sw have the most factor loading with positive sign. Also, GR and V-shale have the most factor loading in Factor-3 that show the effect of shale on gamma ray logs.

For MLP, the optimum model is network with 16 neurons in hidden layer and R is 89.17 %. The results of the model are shown in Figure 4. The correlation between the result of core and MLP network are shown in Figure 5.

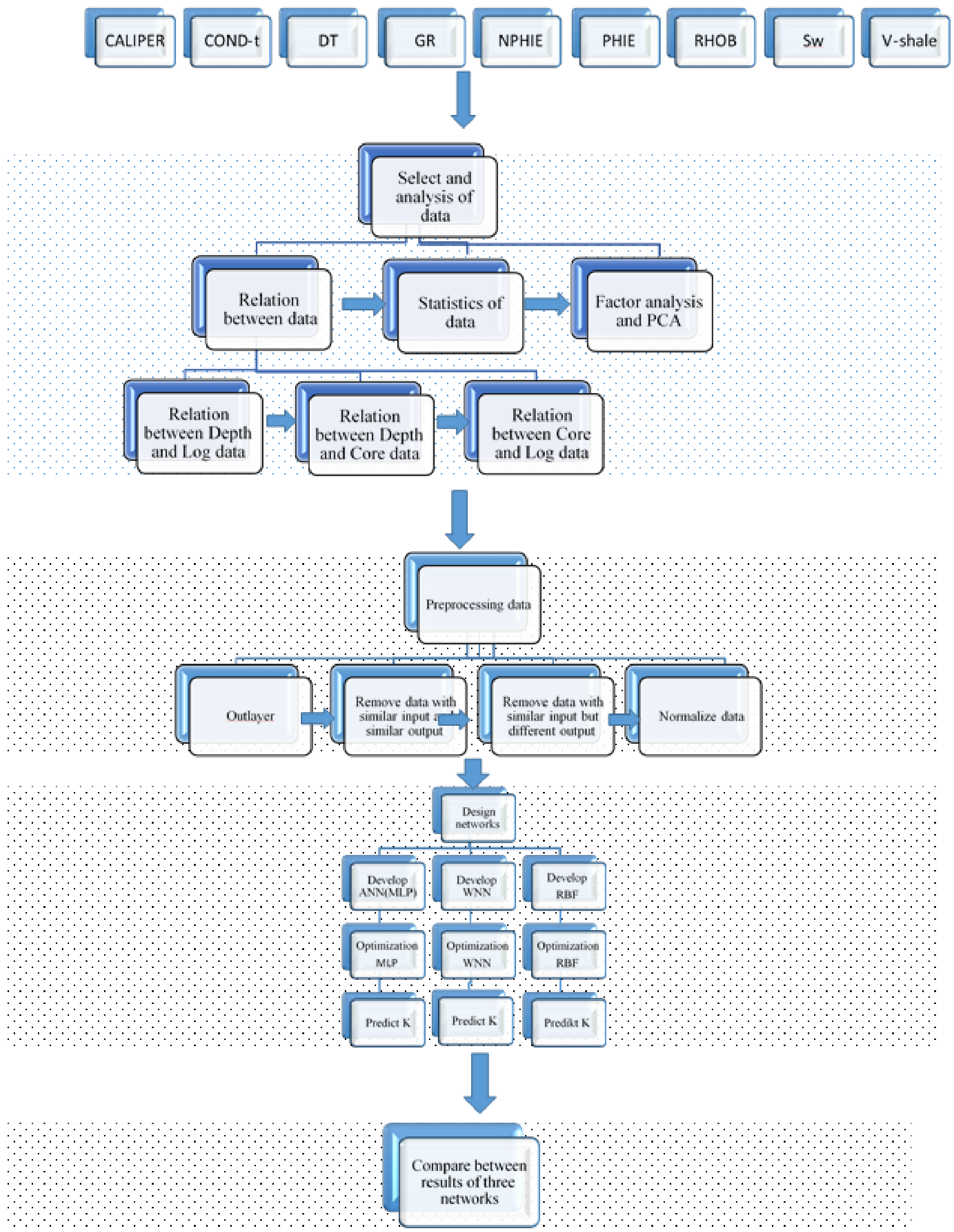


Figure 1. Workflow of the study

We evaluated the performance of RBF models at each step. The optimum model is network with 20 neurons in hidden layer, ϭ=2.5 and R is 89.38 %.

Correlation between targets and outputs are shown in Figure 6 and the correlation between the results of core and RBF network are illustrated in Figure 7.

In Wavenet model, the results show that the optimum model is network with 22 neurons in hidden layer and R is 92.13%.

The results of the models are shown in Figure 8. The correlation between the results of core and Wavenet are shown in Figure 9.

Table 4. PCA results and Eigen values for each principal component

Component	Eigen value	Total-variance (%)	Cumulative (%)
1	3.318	33.182	33.18
2	2.876	28.759	61.94
3	1.864	18.639	80.58
4	0.912	9.120	89.70
5	0.539	5.385	95.09
6	0.204	2.036	97.12
7	0.151	1.507	98.63
8	0.081	0.811	99.44
9	0.058	0.581	100.00

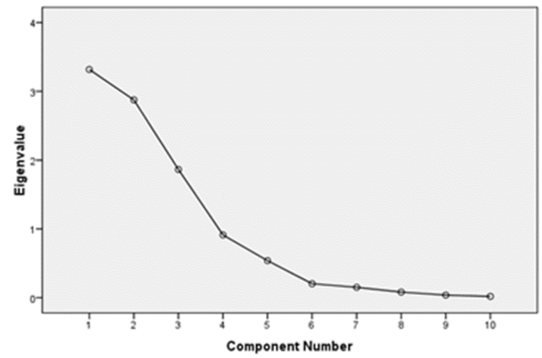


Figure 2. Scree Plot

Table 5. Comparison between MLP, RBF and Wavenet neural networks

Neural network	Number of neurons	MSE	R
RBF	20	0.38346	0.89383
MLP	16	0.39456	0.89166
Wavenet	22	0.261911	0.92129

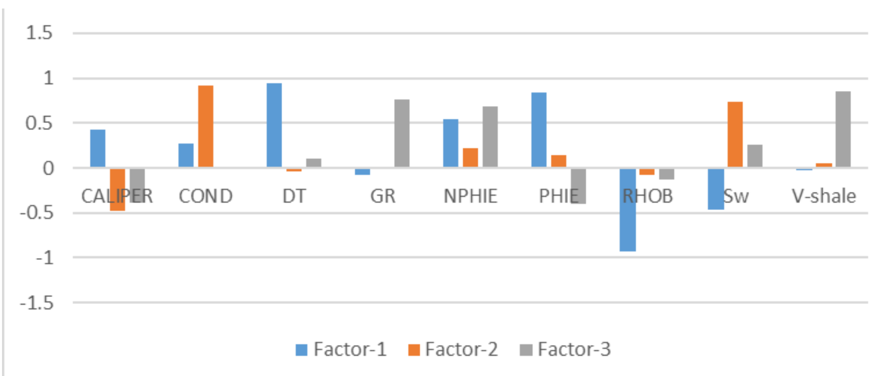


Figure 3. Factor loading coefficients

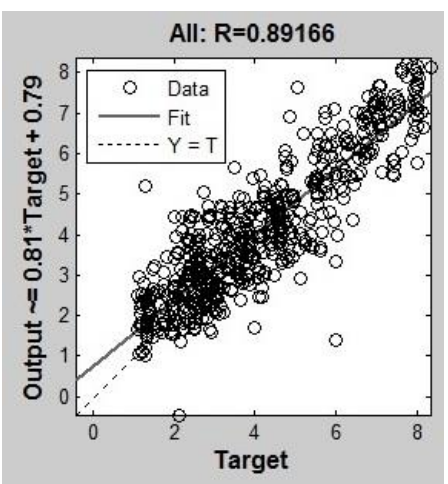


Figure 4. Correlation between targets and outputs for MLP neural network

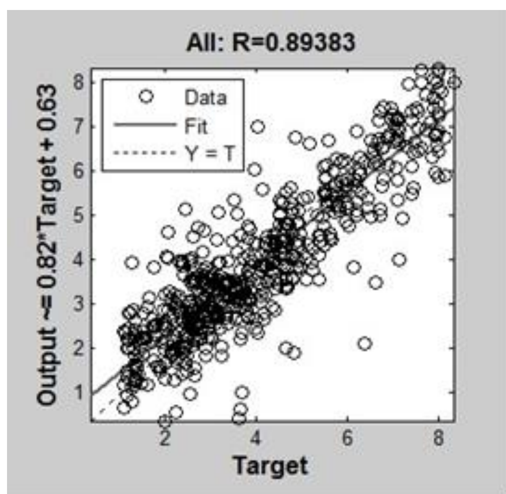


Figure 6. Correlation between targets and outputs for RBF neural network.

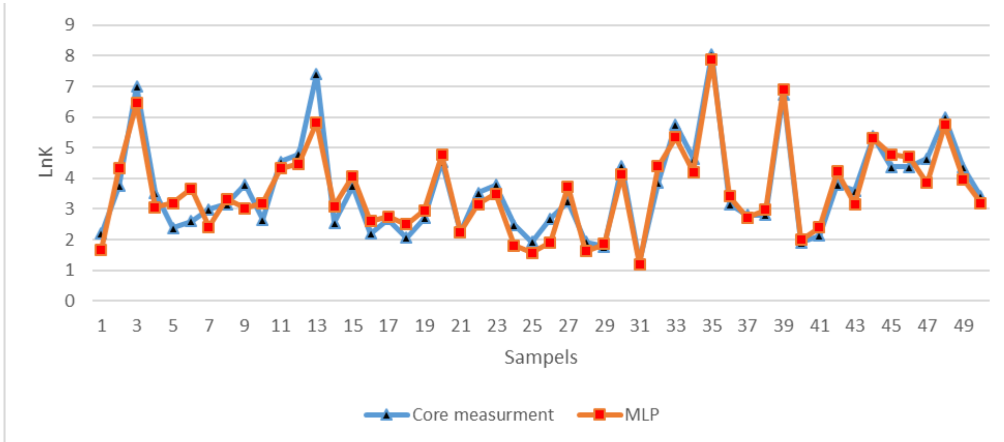
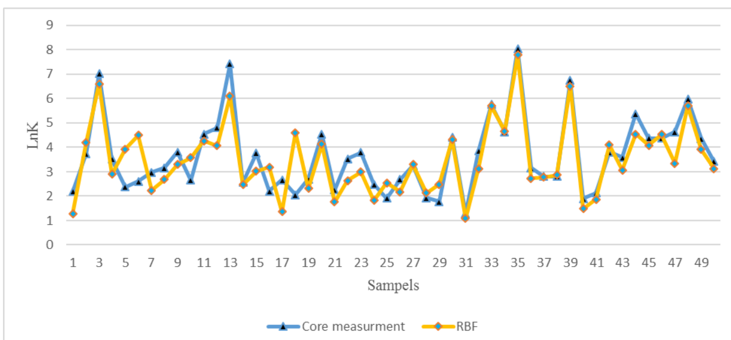


Figure 5. Correlation between core measurement and estimated values from optimized 9-16-1 MLP neural network.



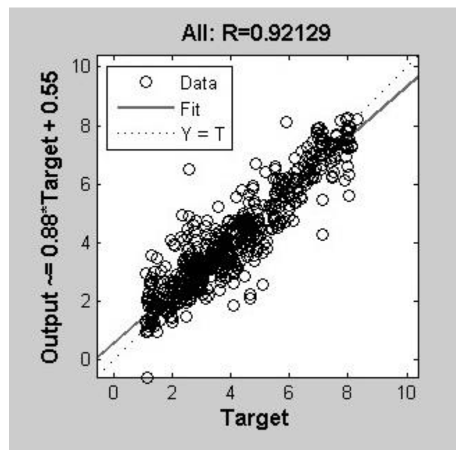


Figure 7. Correlation between core measurement and estimated values from optimized 9-20-1 RBF neural network

Figure 8. Correlation between targets and outputs for Wavenet neural network

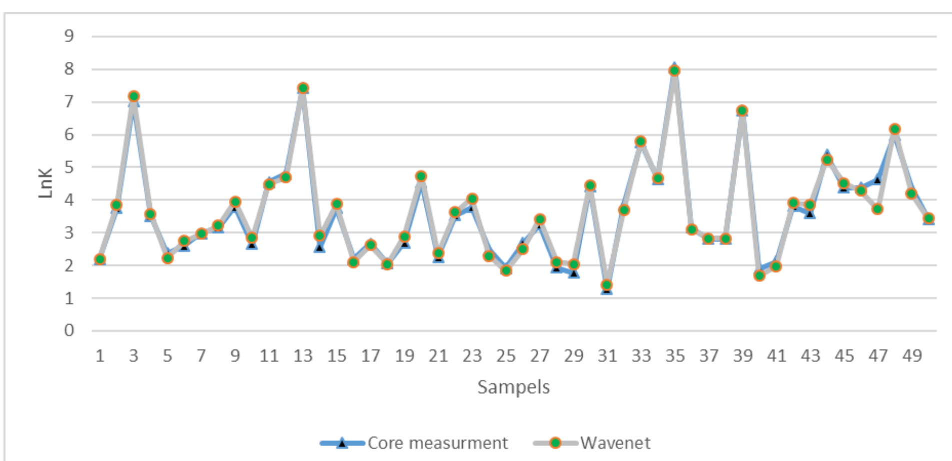


Figure 9. Correlation between core measurement and estimated values from optimized 9-22-1 Wavenet neural network

7.2. Comparison between the results of MLP, RBF and Wavenet models

According to Table 5, Wavenet model has less error and higher Correlation Coefficient (R) than MLP and RBF models. This comparison shows that Wavenet model implemented here is capable of producing results with high accuracy. The correlation between the result of core and results of models are shown in Figure 10.

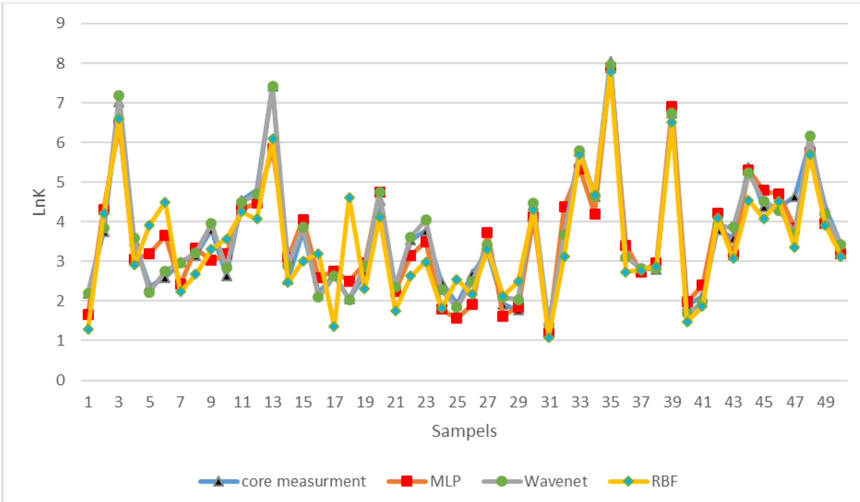


Figure 10. Correlation between results of the networks and core measurement.

8. Conclusions

Well log data and neural network are available tools for indirect estimation of permeability in reservoirs. Preprocessing of data with removing outliers and data with similar input and similar output or similar input and different output can improve correlation between parameters and network training performance. The core data with low permeability value have weak results in ANN and Wavenet, so we can improve estimation of permeability by removing the aforementioned data. When we do not have core data in some cases, ANN can be useful in estimation of permeability. Results of this study show that Wavenet estimates permeability better than MLP and RBF networks. Improvement in the results of Wavenet was done because in this network, wavelet transfer function is used that this function has perpendicular property and good local property. This property causes a quick homogeneity than normal neural network.

Because RBF is a local network and MLP is a global network, results of RBF are better than MLP network. We can use Wavenet for function approximation in static and dynamic nonlinear input-output modeling of processes. Wavenet has high ability to train complex systems.

Wavenet model is very useful for estimation of other petro-physical parameters, such as porosity and water saturation. We recommend using other intelligent methods such as fuzzy Wavenet and comparing its results with other networks. It is suggested to use other data, such as Limestone, Dolomite and Sandstone data, due to the obvious effect of lithology in permeability.

Nomenclature

ANN	*Artificial Neural Network*	*NPHIE*	*Neutron porosity*
BP	*Back propagation*	*PCA*	*Principal Component Analysis*
Cond-T	*True formation conductivity*	*PHIE*	*Effective porosity*
DT	*Sonic travel time*	*RBF*	*Radial basis function*
GR	*Gamma ray*	*RHOB*	*Bulk density*
MLP	*Multilayer Perceptron*	*Sw*	*Water saturation*
MSE	*Mean square error*	*WA*	*Wavelet analysis*
NNs	*Classic sigmoid neural networks*	*WNN*	*Wavelet neural network*

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