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A Novel Approach to Estimate Reservoir Permeability Using Machine Learning Method

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Abstract

Reservoir permeability in upstream of petroleum engineering plays an essential role in crude oil production. Due to the high cost and difficulty in direct measurement of the permeability, having a robust model of this parameter based on the openhole logs and data is preferred. The sonic, volumetric density, gamma ray, total porosity, neutron porosity logs are available in the time of logging and have the highest correlation with reservoir permeability characteristics. To estimate the permeability of the reservoir based on these available data, a new intelligent method of Genetic Algorithm (GA) and Wavelet Neural Network (WNN) is derived. In the developed model, a new objective function has been introduced. For avoiding more complexity of the objective function, the initializing weights of neural network has been done by GA. Then, the training levenberg marquardt algorithm is utilized to update the optimal weighting. In other words, wavelet as activation function of neural network enhances exploitation search abilities of the algorithm and leads to a robust model. In the following, a sample reservoir as a source of data in this field is selected to evaluate the effectiveness of the proposed algorithm in the permeability estimation. For the sake of comparison, two algorithms of BP-ANN and GA-BP, which have been already presented in the literature, are applied for the same data sets and the superiority of developed model in estimation has been illustrated.

Keywords: Permeability Estimation, Wavelet Neural Network, Genetic Algorithm, Logging Data, Reservoir Rock

1. Introduction

Permeability distribution is an essential parameter for reservoir characterization in the exploration and production stage. Also, the amount of oil, water and gas depends on it. The measurement

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procedure of permeability is an intricate process (Zhao et al., 2020). The obtaining of this parameter for the highly heterogeneous reservoirs (via different old ways e.g. core analysis) in the laboratory is very costly and time-consuming. Hence, estimation of this parameter is an important issue to improve reservoir management for the purpose of oil production (Ahmadi and Chen, 2018). Also, to have a good planning for operation, accurate permeability gives the amount of crude oil in the reservoir (da Silva et al., 2015). Estimation of this parameter is generally carried out by using the reservoir accessible geophysical logs (open hole logs) as a source of data in this field.

In the last decade and due to the nonlinearity nature of reservoir permeability and inaccessibility of reservoir rock, a lot of estimation methods based on artificial intelligence have been extensively introduced (Aïfa et al., 2014; Irani and Nasimi, 2011; Iturrarán-Viveros and Parra, 2014; Kaydani et al., 2014). All of these papers focus on optimizing the weights of neural network and promoting the generalization ability of network. Regularization and better generalization of neural network has the most determining factor on the estimation of permeability and should be studied (Aifa, 2014).

Because of the inherent nature of ANN as an universal approximator, it may predict accurately the formation permeability in the highly heterogeneous reservoir (Nasimi et al., 2011; Rafik and Kamel, 2017). Also, ANN with sigmoid activation function cannot sufficiently determine large dimensional problems (Saljooghi and Hezarkhani, 2015). All of these papers used gradient based-back propagation as the training method of neural network while levenberg marquardt based back propagation algorithm is more effective (Baouche et al., 2017).

Some researchers tried to use other intelligent methods to improve the generalization capability of neural networks and combine the fuzzy logic with neural network (Zerrouki et al., 2014).

However, applying these methods may result in slow convergence or to be trapped into a local minimum. In recent years, in order to overcome this drawback, other evolutionary algorithms have been embedded to the ANNs (Alexandridis and Zapranis, 2013; Saljooghi and Hezarkhani, 2014). Augmenting the ANNs with wavelet algorithm (WNN) in these papers improves the local minimum accessing rate with a better accuracy but it has very poor ability in finding global optimum searching. Many types of WNN have been used to optimize the network weights of ANN for permeability estimation and it is shown that using morlet wavelet as an activation function instead of other functions leads to better results in optimization problem around the global optimum (Saljooghi and Hezarkhani, 2014). But, the weakness of this method in finding global optimum and good generalization of net remains.

For more detail, in these gradient-based methods, getting into local optimum with a slow convergence is unavoidable. To overcome this problem, using stochastic optimization methods such as Genetic Algorithm (GA) improves global search capability of network and achieving global convergence quickly (Kaydani et al., 2014; Nasimi and Irani, 2015). In these papers, it is shown that applying GA is a good candidate for escaping the local trapping and estimates the permeability with a good correlation coefficient.

However, statistical methods for permeability estimation has been studied and showed sonic log, density log, neutron log and resistivity log is the most affecting factor on permeability (Esmailzadeh et al., 2017).

In the view of shortcoming of the above mentioned papers; this paper proposes a novel GA-WNN in optimal estimation of the permeability in the oil reservoir. In this regards, the open hole logging data are modelled via Multi-Layer Perceptron ANN (MLP-ANN) based on levenberg marquardt learning algorithm. A salient feature of this modelling is using modified GA in initial weighting of the MLP-ANN procedure. Optimal weighting reduces the prediction error considerably in comparison with random weighting which has been addressed in literature. As another salient feature, while optimizing the weighting of the MLP-ANN, GA the MSE. In other words, this paper proposes a new objective function based on which weighting and MSE are optimized simultaneously. Furthermore, wavelet function is used as an activation function of the MLP-ANN which improves local search ability of the network. This novel combination of global search ability of GA and local search ability of wavelet around the optimum point leads to reliable and robust capability in optimal permeability estimation. To verify the proposed strategy, a practical reservoir is selected as a source of data in this field and our proposed method is used to predict the permeability for the first time in the literature.

2. Theoretical background on WNN and proposed hybrid GA-WNN

2.1. *Wavelet Neural Networks (WNN)*

Artificial Neural Network (ANN) as an effective tool in finding a reasonable model of nonlinear processes have been used when the relation between input and output is not clear. Multilayer Perceptrons is one of the widely used structures which consists of three layers, i.e., input, hidden and output, and is generally trained by a Back Propagation (BP) algorithm.

The main drawbacks of the original ANN tool in complex problems, like estimation of the permeability reservoir, are slow convergence and also stagnation at local minimum points.

For overcoming these issues, this paper recommends the combination of the ANN with wavelet technology which has been already reported in some papers (Alexandridis and Zapranis, 2013). Integration of wavelet into ANN in black-box modelling with a desired degree of accuracy (universal approximator) makes it a powerful tool for analysing problems with severe nonlinearities. In brevity, the primary advantages of WNN, which makes it a suitable model for predicting the permeability from well log data are as follows:

- It requires smaller training amount
- WNN has a fast convergence and also requires fewer nodes.

The employed WNN has similarly three layers in which wavelet is used as activation function in the hidden layer. Generally, the outputs of the hidden layer for the input signals $X_i = (X_1, X_2, \ldots, X_n)$ are calculated as follow:

$$R_j = f\left[\frac{\sum_{i=1}^{n} W_{ij}X_i - a_j}{b_j}\right], j = 1, 2, \ldots, m \tag{1}$$

where, R_j is output value for node j in the hidden layer $j(h_j)$; f is the mother wavelet function; W_{ij} is weight connecting the input layer and hidden layer; a_j is the shift factor, b_j and is the stretch factor for h_j. Finally, the outputs of the WNN is determined as follow:

$$Y_k = \sum_{j=1}^{m} W_{jk}R_j, k = 1, 2, \ldots, l \tag{2}$$

As per equation 2, the output of utilized WNN for estimation of the permeability is derived as follow:

$$Y_1 = \sum_{j=1}^{7} W_jR_j \tag{3}$$

In fact, Y_1 is predicted permeability which is obtained during training and learning processes of the WNN. For this purpose, actual data set of well logging charts, which their detailed information is given in section 3, is used for both input data, i.e., X vector in equation 1 and also actual permeability, hereafter called T_{1k} . T_{1k} means the actual permeability related to kth of the data set.

Figure 1 illustrates the simplified structure of the used three-layers WNN in this paper. As can be seen in Figure 1, the number of neurons in hidden layer, which is called wavelons, has been optimally set to 7. Generally, this number is identified by trial and error process which is not able to guarantee the optimum number. To deal with this issue and as one feature of the proposed strategy, the number of neurons has been optimally obtained via GA algorithm, which is more discussed in the section 2.3. Also, the output layer of network has one neuron (i.e. permeability).

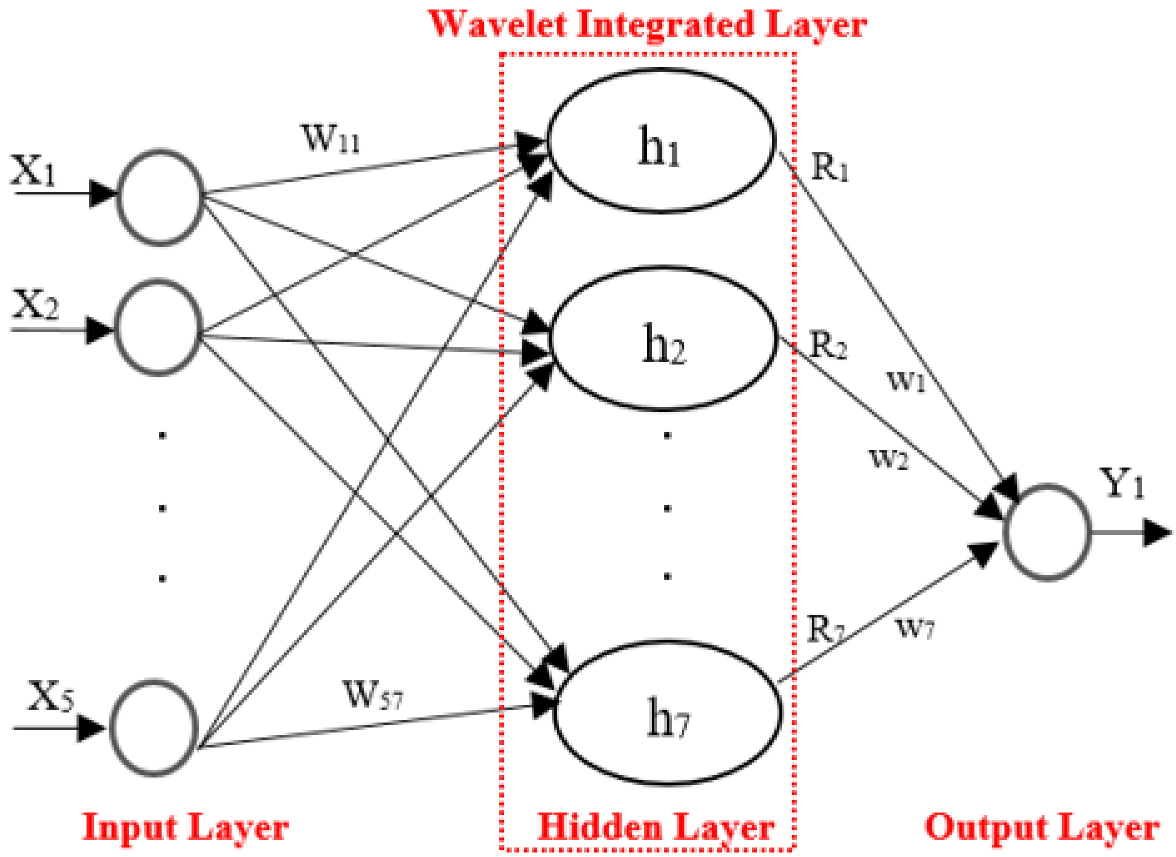

Figure 1: Structure of utilized WNN of the paper

2.2. Morlet Wavelet function

As already mentioned utilization of the WNN improves detection and finding of the optimum point during permeability estimation. In the present study, for the purpose of forecasting permeability a three-layer WNN with morlet function, as mother and daughter wavelet function, is used. The morlet wavelet function is one of the most popular complex wavelets. This function has been selected due to the superiority of this method among others (Saljooghi and Hezarkhani, 2015) and is defined as:

$$\psi(u) = e^{-u^2/2} cos(5u) \tag{4}$$

Figure 2, depicts the mother and daughter morlet based functions. It should be noted that in this work the real part of morlet is used.

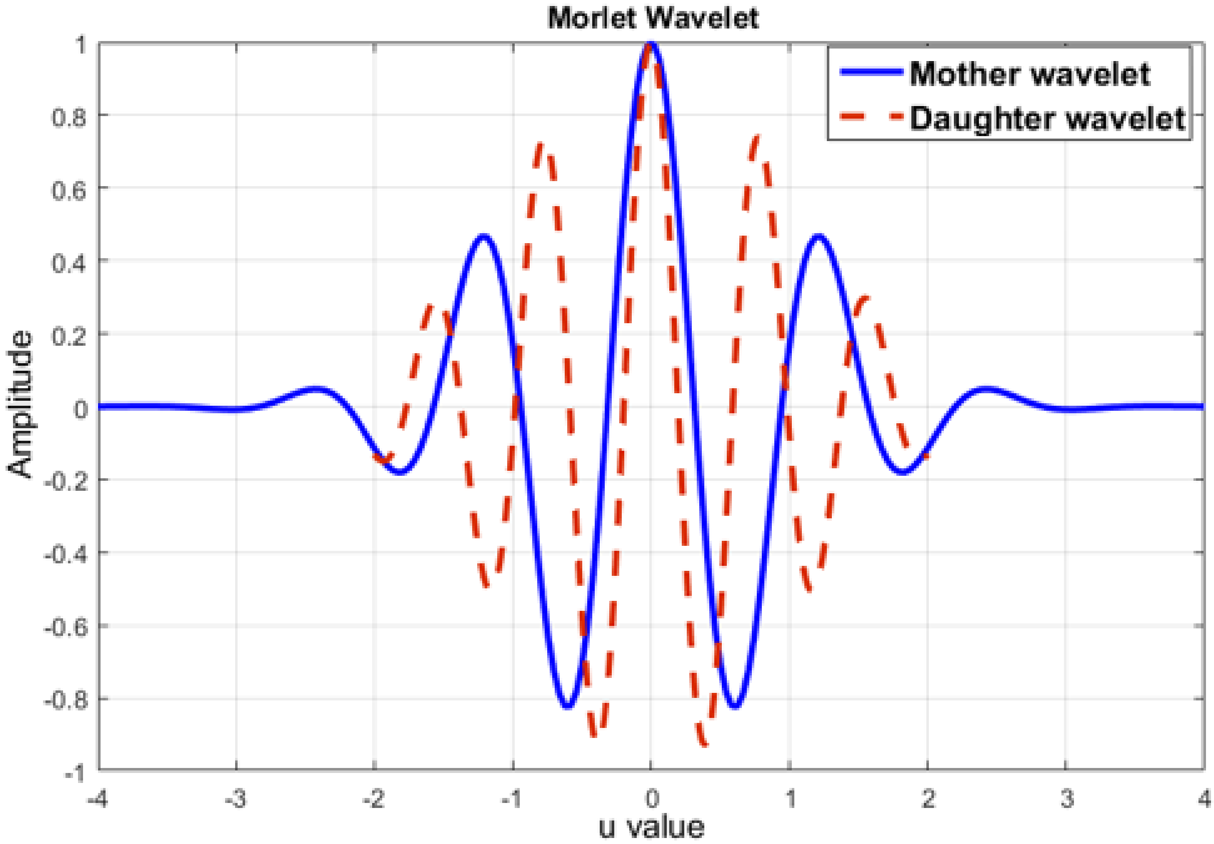

Figure 2: Mother Morlet wavelet with her daughter

2.3. Proposed hybrid GA-WNN

The WNN consists of various parameters, like weights between layers, translation, and dilation of the wavelet function that if they don't adjust well, the accuracy of the predicted model will be decreased. In fact, initialization of such parameters is a vital task for WNN to have fast convergence. Further, selecting related parameters randomly or during trial and error process in complex problems like permeability estimation which is under study of this paper cannot guarantee the accuracy of the model and therefore is not an efficient option. It should also be added that if there exists noisy data among data set, which is very common for experimental data like well logging data, defining parameters encounters error during the training phase.

To solve the aforementioned problem, this paper proposes a robust hybrid GA-WNN algorithm possessing the benefit of optimized parameters and number of neurons and is capable of estimating the permeability of reservoirs from well log data accurately. For this purpose, a new objective function is presented. Flowchart of the proposed algorithm, in which two main subroutines are specified, is briefly depicted in Figure 3 and is illustrated as follows:

- Applying GA for obtaining optimal weighting of the WNN

Due to the complexity of the permeability model, it is difficult to calculate the proper weights of layers or number of the neurons in ANN layers, and generally the trial and error process cannot achieve the best results. Further, the proper selection of the number of neurons in the hidden layer can avoid the overfitting of WNN effectively. GA is a metaheuristic search algorithm inspired by the process of natural selection which due to its easiness has been widely applied for solving a variety of optimization problems. Hence, in this paper GA algorithm is utilized for the purpose of calculating optimized weighing and number of network neurons. In this regard, the Equation (5) is selected as the objective function to calculate the fitness value of the initial population. In fact, within the learning process, while calculating the optimum number of hidden neurons, sum of the mean squared error (MSE) in the output layer is minimized:

$$O.F = min(\alpha \times E_k + \beta \times N_h) \tag{5}$$

$$E_k = \frac{1}{2}\sum_{k=1}^{G}[T_{1k} - Y_{1k}]^2 \tag{6}$$

Where the MSE is shown by E, N_h is the number of hidden layer neurons, α and β are the constant values which are adjusted to normalize two terms of the O.F. in equation (6), the number of training samples is shown by G, the actual value and predicted value of the output are demonstrated by T_{1k} and Y_{1k} , respectively. Note that, as demonstrated in equation (4) the number of output nodes is 1.

In order to make the population more diverse and thus more immune to be trapped in a local optimum, GA uses mutation, crossover and selection operators during optimization process in order to explore the search space faster and more effectively. In this paper, roulette-wheel algorithm is used for selection operator. As per proposed flowchart of Figure 3, the fitness (is the value of the objective function) in the optimization problem is evaluated in every generation and new solutions are then used in the next iteration. Finally, the GA terminates when either a maximum number of generations is produced, or stopping condition is met.

- - Applying wavelet for biasing exploitation search abilities of the algorithm.

Although GA has a good ability in the global exploration and approaching the global optimum, its poor performance in exploitation search around the global optimum point is a considerable drawback, particularly in the ANN integrated problems. Hence, in this paper, wavelet is utilized to update the optimized weights via GA in order to boost exploitation search abilities of the algorithm. In fact, optimal initialization of the WNN leads to fast convergence and accuracy of the algorithm in predicting permeability. As per Figure 3, training of the WNN is based on BP algorithm which is a successful mapping and prediction tool in the petroleum engineering field.

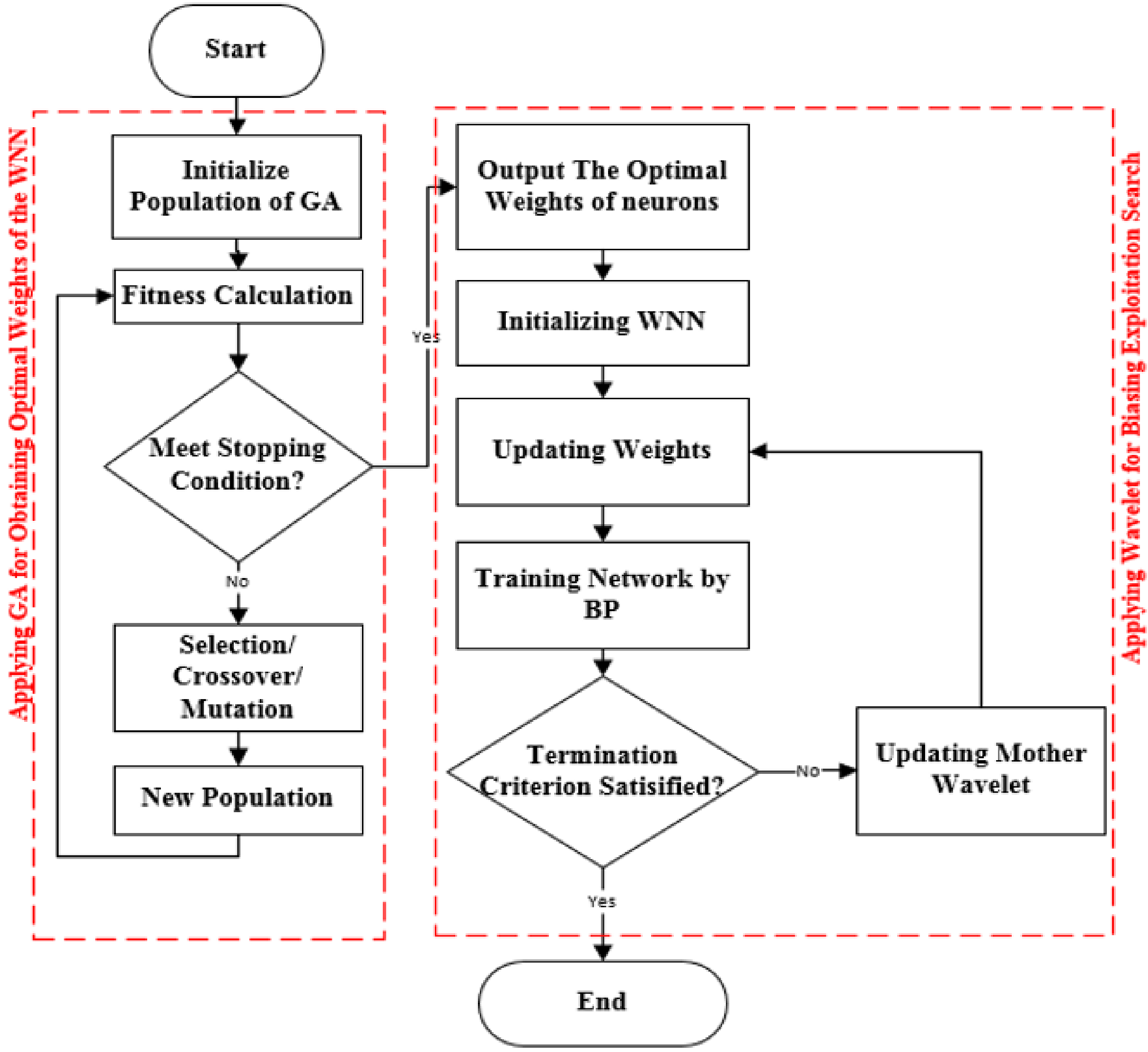

Figure 3: Flowchart of the proposed GA-WNN

The input variables for the prediction of permeability based on the proposed algorithm are: sonic log, volumetric density, gamma ray, total porosity, neutron porosity. It should be noted that the model has been devised in such a way that could be very useful for many different purposes, in this case reservoir management. The constructed neural network in terms of inputs, hidden layer neurons, and output neurons is: 5–7–1. In fact, the optimal hidden neurons in the mid-layer are obtained 7 with morlet activation function in hidden layer.

3. Implementation of the proposed strategy

3.1. Description of the reservoir rock under study for estimation of permeability

The field under study of this paper is Mansuri field which is placed 40 km away from south of Ahwaz city, Iran. Asmari and Bangestan are two reservoirs of this field. The dimension of this field at water oil contact (WOC) in length and width are 30 km and 3.5 km, respectively. Bangestan reservoir, which this paper has focused on, consists of three formations: Ilam, Sarvak, and Kazhdomi. For the sake of permeability estimation, the core data of six wells with numbers of 1, 4, 14, 25, 44, and 54 out of total 57 drilled wells is studied in this paper. The range of permeability are statistically stated between 0.03-45 with standard deviation of 6.43.

3.2. Optimal results and discussion

In this section, the proposed hybrid GA-WNN algorithm is applied to data sets of the Bangestan reservoir to show that it is much more effective in estimating the permeability of the reservoir. Moreover, two algorithms of BP-ANN and GA-BP, which have been already presented in the literature, are also applied for the same data sets used in the GA–WNN model, for the sake of comparison. The parameters of algorithms used in this paper are as follows:

Population size for GA algorithm and generation for GA-WNN is set to 100, crossover and mutation probabilities is adjusted to 0.9 and 0.01, respectively. The value of learning coefficient and momentum correction factor for the BP-ANN training algorithm is set to 0.72 and 0.0011, respectively (Eiben and Smit, 2011).

The predicted and actual permeability values at training and validation phases for three combined models BP-ANN, GA-BP, and GA-WNN are demonstrated in Figures 4, 5, and 6, respectively. It should be noted that, the evaluation of these algorithms is done based on two common parameters, i.e., the mean square error (MSE) and efficiency coefficient R^2 of the estimated permeability. As can be seen in these figures, the designed model by GA-WNN demonstrates a high conformity with the actual value in contrast to other algorithms. Furthermore, comparing MSE and R^2 in three models, confirms the primacy of the proposed model of this paper. The MSE and R^2 results corresponding to each model have been tabulated in Table 1. As can be concluded from the results of the Table 1, efficiency coefficient of the proposed model is 0.9972 which is very satisfactory and has a considerable enhancement rather than two other algorithms. In this regard, the MSE of the estimated permeability of the Bangestan reservoir has decreased to $1.4e-4$. It should be noted that achievement of such a reasonable estimation for permeability is beneficial from the point of view of exploration and production of oil reservoirs.

Table 1: Performances of GA–WNN, GA-BP and BP-ANN in terms of MSE and R^2

Obtained Parameters	**BP-ANN**	**GA-BP**	**GA-WNN**
MSE	2.4e-2	1.4e-3	1.4e-4
R^2	0.5792	0.9207	0.9972

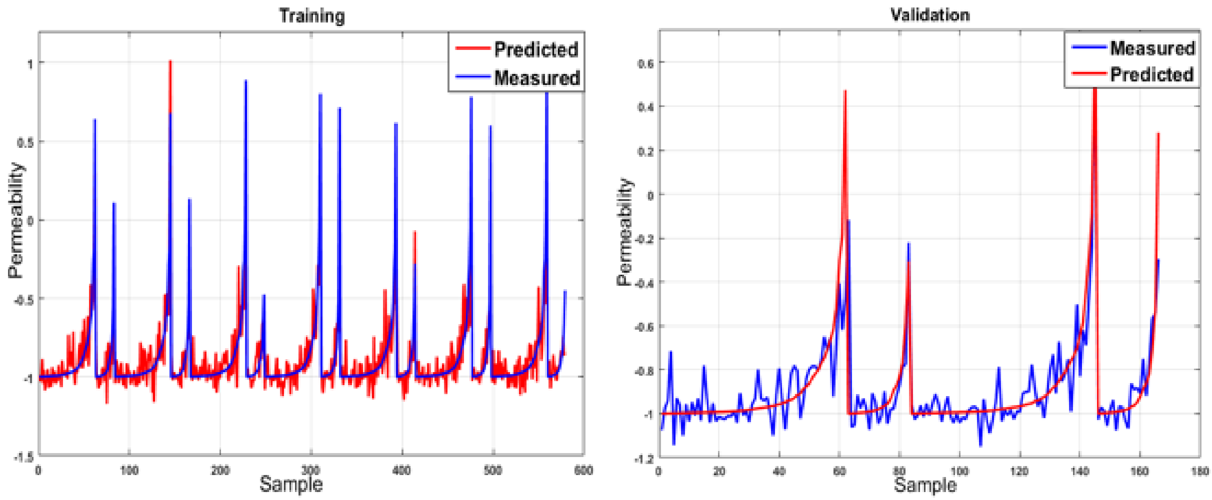

Figure 4: Actual and predicted normalized permeability (BP-ANN)

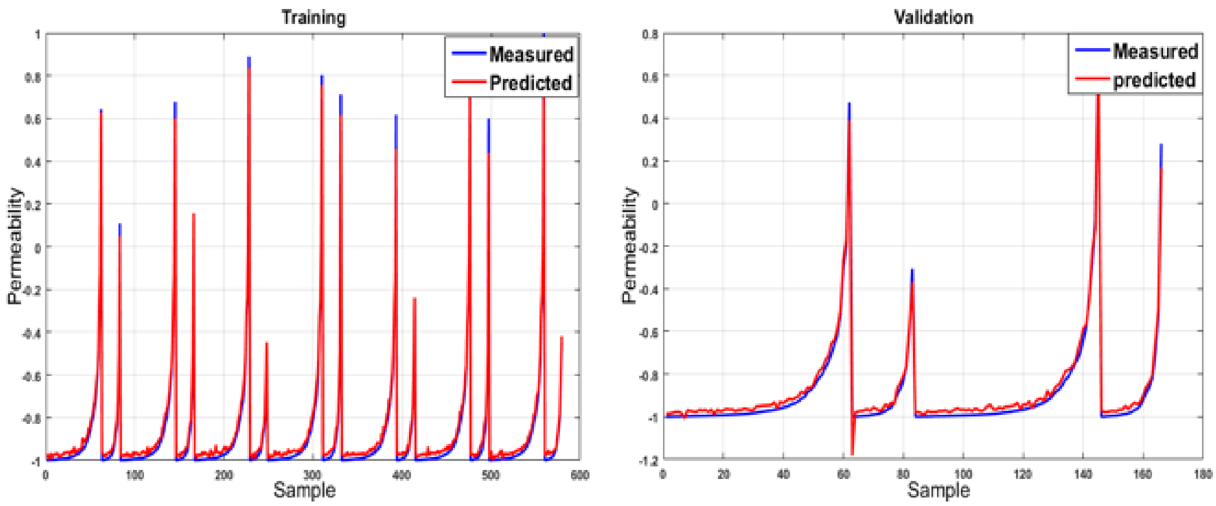

Figure 5: Actual and predicted normalized permeability (GA-BP)

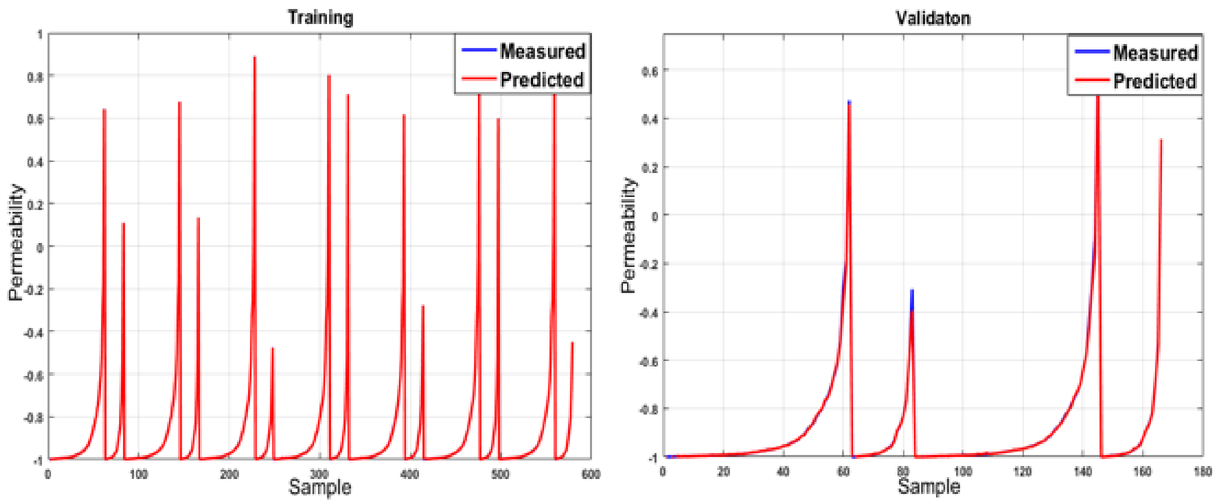

Figure 6: Actual and predicted normalized permeability (GA-WNN)

Further, the scatter diagrams related to models of BP-ANN, GA-BP, and GA-WNN are also depicted in Figures 7, 8, and 9, for the comparison purpose between the real and estimated permeability values in different algorithms. Again it can be concluded that the better results are achieved via presented GA-WNN algorithm of this paper. This is due to the combining of some features of GA with the ability of wavelet function around the global optimum which improves the ability of the GA-WNN. This feature has made the proposed model a robust nonlinear mapping model which, irrespective of type of rock in the reservoir, can be applied for various reservoirs.

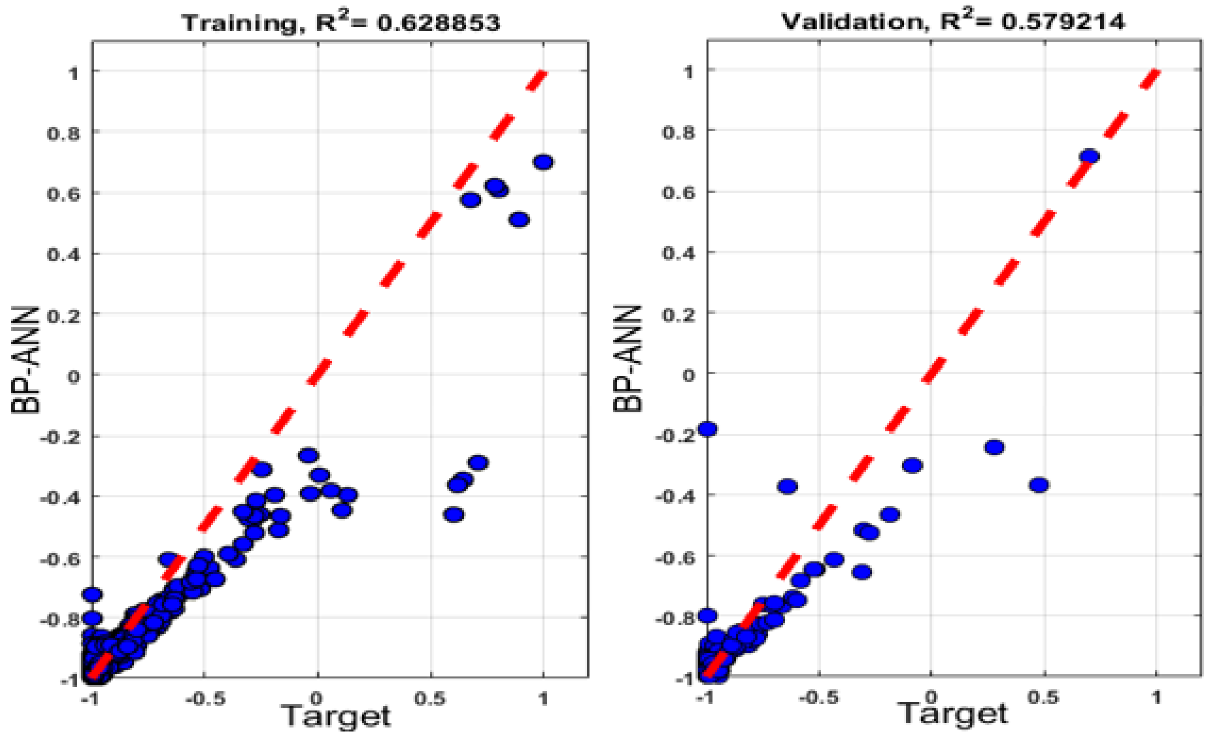

Figure 7: The value of R^2 for training and validation phases (BP-ANN)

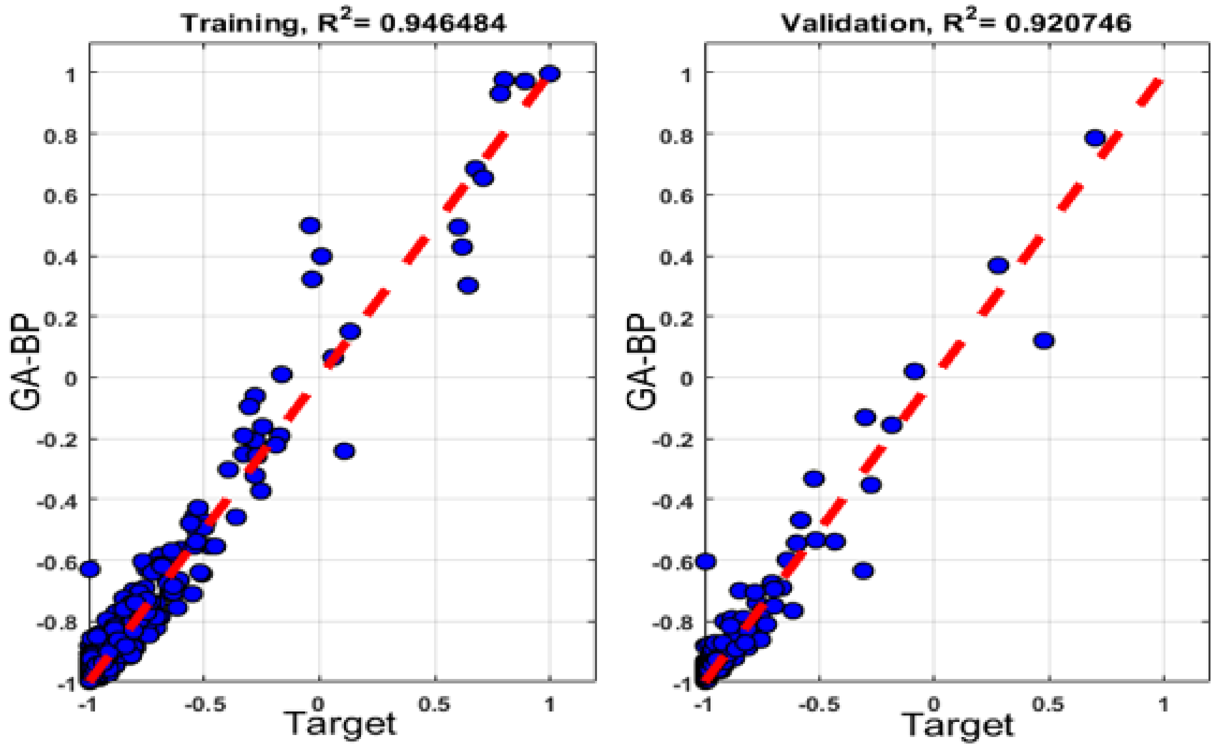

Figure 8: The value of R^2 for training and validation phases (GA-BP)

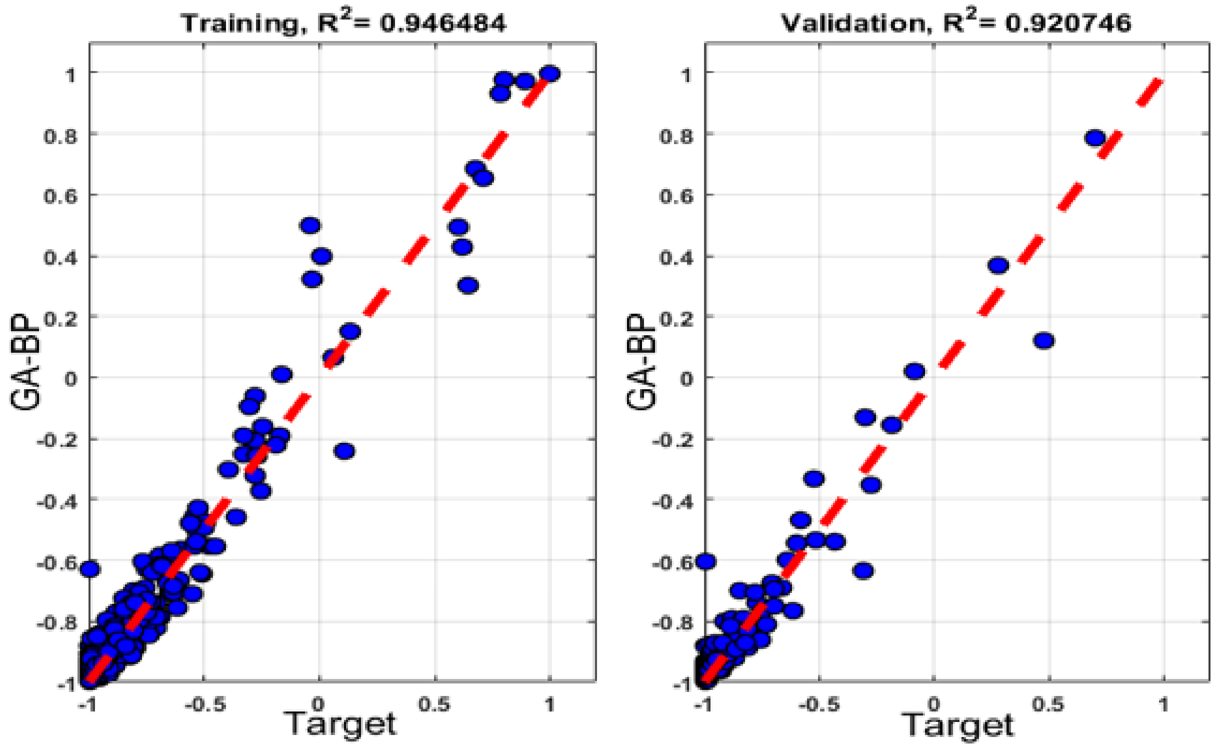

Figure 9: The value of R^2 for training and validation phases (GA-WNN)

4. Conclusions

The permeability of the oil reservoir is an essential parameter in petroleum engineering which due to its nonlinearity nature cannot be measured experimentally and should be estimated. Hence, the accuracy and efficiency of the estimation methods is a challenging task. In this regard, this paper proposed a new hybrid GA-WNN model for estimating this parameter. The proposed model effectively combines GA for the global search and wavelet activation function for improving local search ability of ANN using BP learning algorithm (GA-WNN). This model is devised to irrespective of type of rock in reservoir can be applied for various reservoirs. The effectiveness of the algorithm was assessed by applying on a practical reservoir formation rock, named Bangestan. Furthermore, two algorithms of BP-ANN and GA-BP, which have been already presented in the literature, were also applied for the same data sets, for the sake of comparison. The obtained results confirmed that GA-WNN led to lowest MSE and highest efficiency among three studied models. This matter shows that the proposed model, as a robust nonlinear mapping model, is a promising solution for measuring and estimating permeability of the oil reservoir.

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