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Prediction of permeability in a tight gas reservoir by using three soft computing approaches: A comparative study

Sadegh Baziar [a,*], Mehdi Tadayoni [b], Majid Nabi-Bidhendi [c], Mohsen Khalili [a]

[a] Department of Petroleum Engineering, Amirkabir University of Technology, Tehran, Iran
[b] National Iranian Oil Company, Tehran, Iran
[c] Institute of Geophysics, University of Tehran, Tehran, Iran

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ABSTRACT

Permeability is the most important petrophysical property in tight gas reservoirs. Many researchers have worked on permeability measurement methods, but there is no universal method yet which can predict permeability in the whole field and in all intervals of the wells. So artificial intelligence methods have been used to predict permeability by using well log data in all field areas. In this research, Multilayer Perceptron Neural Network, Co-Active Neuro-Fuzzy Inference System and Support Vector Machine techniques have been employed to predict permeability of Mesaverde tight gas sandstones located in Washakie basin in USA. Multilayer Perceptrons are the most used neural networks in regression tasks. Co-Active Neuro-Fuzzy Inference System is a method which combines fuzzy model and neural network in a manner to produce accurate results. Support Vector Machine is a relatively new intelligence method with great capabilities in regression and classification tasks. Each method has advantages and disadvantage and here their capability in predicting permeability has been evaluated. In this study, data from three wells were used and two different dataset patterns were constructed to evaluate performances of the models in predicting permeability by using either previously seen data or unseen data. The most important aspect of this research is investigation of capability of these methods to generalize the training patterns to previously unseen data. Results showed that all methods have acceptable performance in predicting permeability but Co-Active Neuro-Fuzzy Inference System and Support Vector Machine performs so better than Multilayer Perceptron and predict permeability more accurate.

1. Introduction

The increase in energy demand has led operators to exploit all hydrocarbon resources, including tight gas reservoirs. Tight gas is the term commonly used to refer to low permeability reservoirs that produce mainly dry natural gas (Naik, 2008). Tight Gas Reservoir is often defined as a gas bearing sandstone or carbonate matrix which exhibits in-situ permeability to gas of less than 0.10 millidarcys (Naik, 2008).

Determination of petrophysical properties of tight gas reservoirs is a key element in development and production from them. Permeability is one of the most challenging parameters to be measured. It is a property of reservoir rock and controls the fluid flow. This is notable that permeability measurement in tight gas reservoirs because of their small values of permeability is more difficult than conventional reservoirs. There are some ways to measure permeability of reservoir.

Abbreviations: AAE, average absolute error; ANN, artificial neural network; BP, back-propagation; C, regularization parameter; CANFIS, Co-Active Neuro-Fuzzy Inference System; CART, classification and regression trees; DT, sonic travel-time log; ERM, empirical risk minimization; GAPI, gamma ray log unit; GR, gamma ray log; g/cm^3, density unit; m, meter; md, millidarcy; MLFF, multilayer feed forward network; MLP, multilayer perceptron; MSE, mean squared error; NFIS, neuro-fuzzy inference system; NPHI, neutron porosity log; OHMM, electrical resistance unit; r, correlation coefficient; RBF, radial basis function; RHOB, bulk density log; RT, resistivity log; SRM, structural risk minimization; SVC, support vector classification; SVM, Support Vector Machine; SVR, support vector regression; TSK, Takagi–Sugeno–Kang; US/F, sonic travel-time log unit; VC, Vapnik–Chervonenkis; X_{max}, maximum value of parameter; X_{min}, minimum value of parameter; X_n, n^{th} parameter.

* Corresponding author. Tel.: +98 9380162720.
E-mail address: baziar@aut.ac.ir (S. Baziar).

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Permeability measurement in well cores under high confining pressure in a laboratory is a common way to estimate permeability structure at depths (Tadayoni and Valadkhani, 2012). Laboratory measurement can provide accurate values of permeability, but this method has some limitations. Cores are few in number and not drilled in all wells of the field. Also, cores are not drilled in all intervals of a well and cannot present the reservoir comprehensively. On the other hand, well logs are usually available for all wells and provide continuous information across the well. So, it can be a good idea to create relationships between well logs and permeability. Here are some examples of prediction of permeability from well logs.

Artificial neural networks have being extensively used for prediction of petrophysical and reservoir properties from well log data (Mohaghegh et al., 1995; Wiener et al., 1995; Huang et al., 2001; Bhatt, 2002; Asadisaghandi and Tahmasebi, 2011; Gorzalczany and Gradzki, 2000; Karimpouli et al., 2010; Mohaghegh et al., 2001; Nikravesh, 2004; Sahimi, 2000; Mollajan and Memarian, 2013). Also, previous researches show that artificial neural networks can be a powerful tool for predicting permeability (Tahmasebi and Hezarkhani, 2012; Aminian and Ameri, 2005; Aminian et al., 2001; Wong et al., 2000; Al-Anazi and Gates, 2010c; Irani and Nasimi, 2011; Jamialahmadi and Javadpour, 2000; Al-Anazi and Gates, 2010d).

The most important property of ANNs is their ability to approximate virtually any function in a stable and efficient way. By using ANNs, it is possible to create a platform on which different models can be constructed.

Neuro-fuzzy models have gained many attentions recently due to their numerous advantages. Co-Active Neuro-Fuzzy Inference System (CANFIS) shows more flexible model structure that can be used for non-linearity between the model input and output and complex interactions between them. CANFIS has been employed in various types of problems (Aziza et al., 2013; Parthiban and Subramanian, 2008; Aytek, 2009; Chen et al., 2008; Benecchi, 2006; Tabari et al., 2012), but it has been used rarely in petroleum engineering problems. Saemi and Ahmadi modeled permeability from well logs by using CANFIS (Saemi and Ahmadi, 2008).

Recently, Support Vector Machines (SVMs) have gained popularity in regression and classification because of their privileged generalization performance. The formulation of SVM is based on the structural risk minimization (SRM) inductive principle where the empirical risk minimization (ERM) inductive principle and the Vapnik–Chervonenkis (VC) confidence interval are simultaneously minimized (Vapnik, 1982, 2000; Vapnik and Chervonenkis, 1974). SVMs have been used in variety of petroleum engineering fields and have shown acceptable performance. Yue and Wang used SVM to predict sandstone thickness of oilfield fan from seismic waveform (Yue and Wang, 2007). Al-Anazi and Gates used SVM to classify litho-facies in a heterogeneous reservoir (Al-Anazi and Gates, 2010a). Mollajan and Memarian employed SVM to predict water saturation (Mollajan et al., 2013). SVM also has been used for prediction of permeability (Al-anazi et al., 2009; Saffarzadeh and Shadizadeh, 2012).

In this research, three methods including Multilayer Perceptron Neural Network (MLP), Co-Active Neuro-Fuzzy Inference System, and Support Vector Machine have been used to predict permeability in Mesaverde tight gas reservoir located in Washakie basin, USA and Results obtained from all methods has been compared.

1.1. Multilayer Perceptron Neural Network

Multilayer perceptrons (MLPs) are layered feed-forward networks typically trained with static back-propagation. They are also called multilayer feed forward networks (MLFF). Multilayer perceptron (MLP) networks are currently the most used neural networks.

Multilayer perceptron consists of one input layer, one or more hidden layer(s) and one output layer (Hornik et al., 1989). One hidden layer is usually suitable and using more hidden layers rarely improves the model (Sherrod, 2008). The number of neurons in input layer is equal to the number of input parameters and output layer has neurons as the number of output parameters. The number of hidden layer(s) neurons should be selected carefully because little number of neurons may not be able to control the complexity of model and high number of neurons may cause complexity and overfitting problems. It has been mathematically proven that a network with a hidden layer of arbitrary large number of nonlinear neurons can approximate any continuous nonlinear function over a compact subset to any desirable accuracy (Hornik et al., 1989; Al-Anazi and Gates, 2010b).

MLP utilizes a supervised learning technique called back-propagation for training the network (Rosenblatt, 1961; Rumelhart et al., 1985). The back-propagation algorithm is the first training method for neural networks (Rumelhart et al., 1985; McClelland, 1986). The training process consists of estimating weights that minimize deviations between network outputs and actual data. The deviations are then propagated backwards through the network and weights are adjusted to reduce the error (Al-Anazi and Gates, 2010b).

MLP is previously used for prediction of some petrophysical properties and (Bhatt, 2002; Pandya and Szabo, 1998; Majdi et al., 2010; Ouadfeul and Aliouane, 2012; Baneshi et al., 2013; Boadu, 2001) is also employed for estimating permeability several times (Jamialahmadi and Javadpour, 2000; Wong et al., 2000; Rezaee et al., 2006; Aliouane et al., 2012; Tahmasebi and Hezarkhani, 2012; Al-anazi et al., 2009).

1.2. Co-Active Neuro-Fuzzy Inference System

Co-Active Neuro-Fuzzy Inference System (CANFIS) is one of the most powerful tools which processes the advantages of both artificial neural network and fuzzy logic. A fuzzy system is capable of making fuzzy associations from representative numerical samples (Wang, 1994). Neuro fuzzy system combines the advantage of fuzzy systems.

CANFIS combines Classification and Regression Trees (CART) and the Neuro-Fuzzy Inference System (NFIS) (Parthiban and Subramanian, 2009). CANFIS bears a close relationship to the computational paradigms of radial basis function (RBF) networks and modular networks (Parthiban and Subramanian, 2009).

One basic component of CANFIS is a fuzzy node which uses membership functions to the input nodes. Two common membership functions are bell and Gaussian. The second basic component of CANFIS is a modular network that applies functional rules to the inputs (Singh et al., 2007). CANFIS also has a combiner axon that applies the MFs outputs to the modular network outputs. While fuzzy logic provides an inference mechanism under cognitive uncertainty, computational neural networks offer exciting advantages, such as learning, adaptation, fault-tolerance, parallelism and generalization (Fullér, 1995).

CANFIS enables to obtain more than one outputs and has the advantage of non-linear rule formations (Hardalac et al., 2004). The most important limitation of CANFIS is that it cannot predict values outside the ranges of data used in training. So based on the prediction data, training database should be selected carefully.

1.3. Support Vector Machine

Support Vector Machines (SVMs) are learning machines implementing the structural risk minimization inductive principle to obtain good generalization on a limited number of learning patterns (Vapnik, 2000; Al-anazi et al., 2009; Basak et al., 2007). SVM is a learning system using a high dimensional feature space. It yields prediction functions that are expanded on a subset of support vectors (Cortes and Vapnik, 1995). Operating in high dimensional feature spaces is provided by using kernel functions. SVMs attempt to minimize the probability of misclassifying test data, unseen by the model, drawn randomly from a fixed but unknown probability distribution (Al-Anazi and Gates, 2010d). Support Vector Machines are characterized by employing kernels, absence of local minima, and sparseness of the solution and capacity control obtained by acting on the margin, or on number of support vectors.

Support Vector Machines have two main subdivisions: support vector classification (SVC) and support vector regression (SVR). Statistical Learning Theory has provided a very effective framework for classification and regression tasks Involving features. Support Vector Machines (SVMs) are directly derived from this framework (Basak et al., 2007; Vapnik, 2000). SVR works by nonlinearly mapping the input space into a high-dimensional feature space and then running the linear regression in the output space (Saffarzadeh and Shadizadeh, 2012). Learning by small number of training data is one of the most interesting properties of SVM (Al-Anazi and Gates, 2010c; Saffarzadeh and Shadizadeh, 2012; Gholami et al., 2012). Because of this feature SVM can be applicable in petrophysical studies, because there are usually little information in each oil field and their database has few number of data points.

2. Material and methods

The data used for this study is obtained from Measverde tight gas sandstones located in Washakie basin in USA. Mesaverde Group sandstones represent the principal gas productive sandstone unit in the largest Western U.S. tight gas sandstone basins.

In this research, log information from three wells, 1, 2 and 3 were used. Well 1 has a total of 87 data points, well 2 has 54 data points and well 3 has 20 data points. For evaluating the capability of methods to predict permeability, 2 dataset patterns were built. In the first dataset pattern, models built with training data were tested with data points in available in training data. As shown in Table 1 there are 4 datasets in this pattern. In the second dataset pattern which is described in Table 2, models trained with training datasets were tested with unseen data to evaluate their generalization capability to generalize the results to new unseen data.

Each training pattern consists of log data including gamma ray log (GR), neutron porosity log (NPHI), resistivity log (RT), bulk density log (RHOB), and sonic travel-time log (DT) as input vectors, and core-based permeability as a scalar output. The ranges of the used data for different groups are as shown in Table 3:

Table 1
Training and testing dataset up for seen data.

Dataset no	Training well(s)	Testing well
1	1	1
2	2	2
3	1 and 2	1
4	1 and 2	2

Table 2
Training and testing dataset up for unseen data.

Dataset no	Training well(s)	Testing well
1	1	2
2	2	1
3	1	3
4	2	3
5	1 and 2	3

In order to reduce the large differences in the values of each parameter, all dataset values were normalized between 0 and −1 using Equation (1).

$$X_n = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

Different models of regression (MLP, CANFIS and SVM) were constructed to predict permeability. Neurosolution intelligent software was used for modeling in this study.

MLP neural network models constructed here had 3 layers one input, one hidden and one output. 4 processing elements were chosen for hidden layer. The Tanh Axon nonlinearity function was used to specify the behavior of processing elements and Momentum rule was selected learning rule for hidden and output layers. For training, 1000 epochs were regarded as the Maximum Epochs which specifies how many iterations (over the training set) will be done if no other criterion kicks in. Termination of the training was based on mean squared error (MSE). Incremental function was selected as a controlling tool in termination of training. The Incremental function terminates when the change in MSE from iteration to the next is less than the threshold. Batch learning method was selected as weight update manner which updates the weights after the presentation of the entire training set. 3 runs were performed for training and validation and the best models were built through these runs. 10-fold cross validation method was used for validation.

For constructing CANFIS models, Generalized Bell function was selected as membership function and each input was fed into 3 unique Bell functions. Takagi–Sugeno–Kang (TSK) model was selected as fuzzy structure. TSK models are a powerful tool for function approximation problems given a dataset of input/output data (Herrera et al., 2005). Axon transfer function was used as nonlinearity function of output layer and Momentum rule was selected as learning rule. For training, 1000 epochs were regarded as the Maximum Epochs. Termination of the training was based on MSE. Incremental function was selected as a controlling tool in termination of training. Also, Batch learning method was selected as weight update manner. 3 runs were performed for training and validation. 10-fold cross validation method was used for validation.

Table 3
The ranges of parameters.

	Well no. 1	Well no. 2	Well no. 3
Gamma ray (GAPI)	25.076–119.483	34.107–82.086	33.969–74.375
Bulk density (g/cm^3)	1.999–2.677	2.444–2.665	2.469–2.639
Neutron porosity	0.072–0.648	0.072–0.704	0.105–0.143
Resistivity (OHMM)	15.63–139.68	6.486–16.029	10.961–27.922
Sonic travel-time (US/F)	61.35–104.78	62.167–77.674	66–74.625
Depth (m)	3233.62–3307.69	3861.82–3878.28	3784.09–3799.64
Permeability (md)	0.01–0.16	0.02–0.1	0.01–0.08

Table 4
Errors formulation.

Accuracy measure	Mathematical expression
Correlation coefficient, r	$\frac{\sum_{i=1}^{l}(y_i-\bar{y}_i)(\hat{y}_i-\bar{\hat{y}}_i)}{\sqrt{\sum_{i=1}^{l}(y_i-\bar{y}_i)^2\sum_{i=1}^{N_p}(\hat{y}_i-\bar{\hat{y}}_i)^2}}$
Average absolute error	$\frac{1}{l}\sum_{i=1}^{l}\lvert y_i-\hat{y}_i\rvert$
Mean squared error	$\frac{1}{n}\sum_{i=1}^{l}(\hat{Y}_i-Y_i)^2$

For constructing SVM models, sigmoid kernel function was used, because it has proved its better performance comparing other kernel functions before (Al-Anazi and Gates, 2010b, 2010c). 3 runs were performed for training and validation. 10-fold cross validation method was used for validation. The accuracy of an SVM model depends on a true setting of the parameters C, ε and the kernel parameters. The problem of optimal parameter selection is more complicated by the principle that an SVM model complexity depends on all three parameters. While designing an SVM, the user is confronted with the choice of which kernel to use, and for a given kernel, how to adjust the parameter(s). Based on researches done with Al-Anazi and co-workers (Al-Anazi and Gates, 2010c; Al-anazi et al., 2009; Al-Anazi and Gates, 2010b), optimal values of parameters were selected by simultaneous use of grid search and pattern search methods. A grid search tries values of each parameter across the specified search range using geometric steps (Sherrod, 2008). A pattern search starts at the center of the search range and makes trial steps in each direction for each parameter. If the fit of the model improves, the search center moves to the new point and the process is repeated. If no improvement is found, the step size is reduced and the search is tried again (Sherrod, 2008). The pattern search stops when the search step size is reduced to a specified tolerance (Sherrod, 2008). In simultaneously using grid search and pattern search, the grid search is performed first. When the grid search finishes, a pattern search begins over a narrow search range surrounding the best point found by the grid search (Al-Anazi and Gates, 2010c, 2010b).

To compare methods, each one was used to create a predicted value of permeability and the difference between each predicted and core-based value was assessed by correlation coefficient (r), average absolute error (AAE) and mean squared error (MSE) as defined in Table 4.

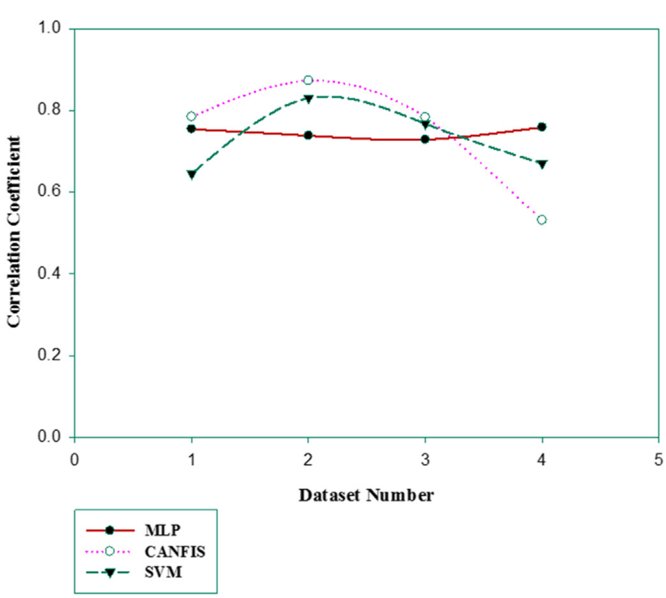

Fig. 1. Comparison of MLP, CANFIS and SVM in predicting permeability by using previously seen data.

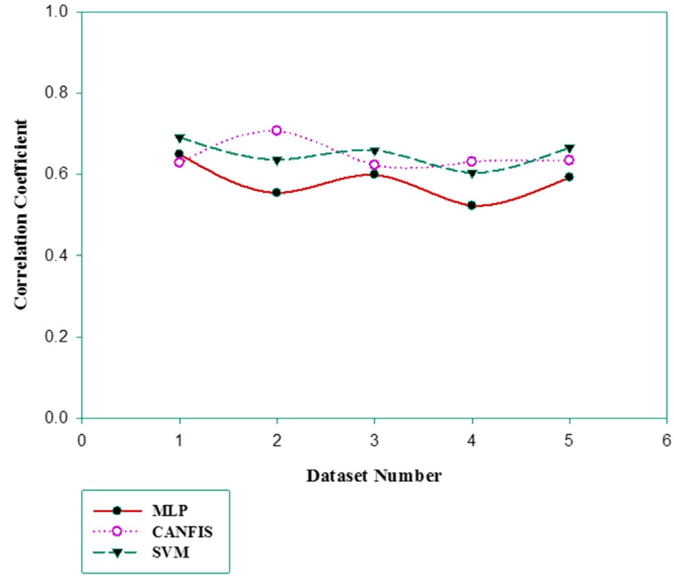

Fig. 2. Comparison of MLP, CANFIS and SVM in predicting permeability by using previously unseen data.

3. Results and discussion

The correlation coefficient for the estimation of permeability by using MLP, CANFIS and SVM methods are demonstrated in Fig. 1 and Fig. 2. Fig. 1 shows capability of methods to estimate permeability by using seen data which were used to train the models. Fig. 2 represents the results of predicting permeability by using previously unseen data to compare their generalization capability.

It can be understood from Fig. 1 that all methods used have similar results and exhibit reliable performance in estimating permeability of data which were used in training. CANFIS overly performs better in predicting permeability rather than MLP and SVM. It is also notable that MLP and SVM have similar performances.

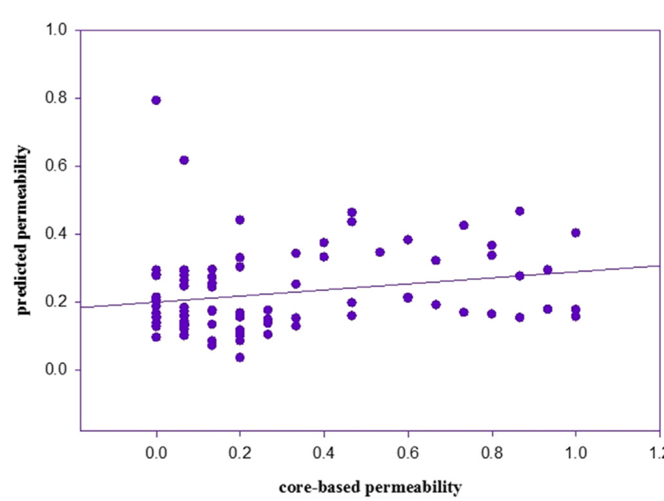

Fig. 3. Scatter plots of predictions made by MLP in dataset 1.

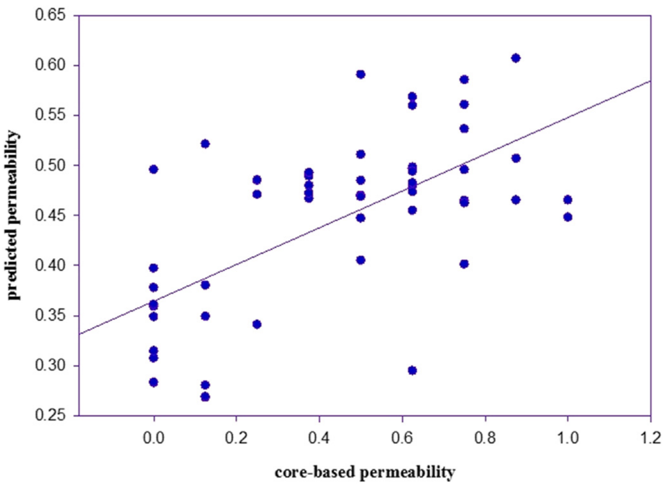

Fig. 4. Scatter plots of predictions made by CANFIS in dataset 1.

Fig. 2 reveals that SVM and CANFIS methods have similar performances and create better results than MLP. As it is demonstrated in Fig. 2, in Datasets 1, 3 and 5, SVM is the best predictor and CANFIS performs as the best in Datasets 2 and 4.

Scatter plots for the results of prediction of permeability in dataset 1 is demonstrated in Fig. 3, Fig. 4 and Fig. 5.

Fig. 6 shows the results of estimating permeability of seen data by SVM in dataset 2. It can be seen that predicted permeability curve has a form like core-based permeability curve and in each data point difference between two values is negligible. It reveals the superior learning of SVM from training data.

Fig. 7 exhibit results of prediction of permeability of unseen data by CANFIS in dataset 3. It is understood that CANFIS tries to generalize patterns form training data to test data and it has a continuous manner in predicting permeability from test data and its results are similar to core-based results except for points which exhibit abnormal behavior. It represents the acceptable performance of CANFIS in predicting permeability from unseen data.

To compare the models, the average percentage difference in error between each technique and the actual data was computed through analysis of AAE and MSE error measurements. Table 5 shows the average errors (AAE and MSE) of MLP, CANFIS and

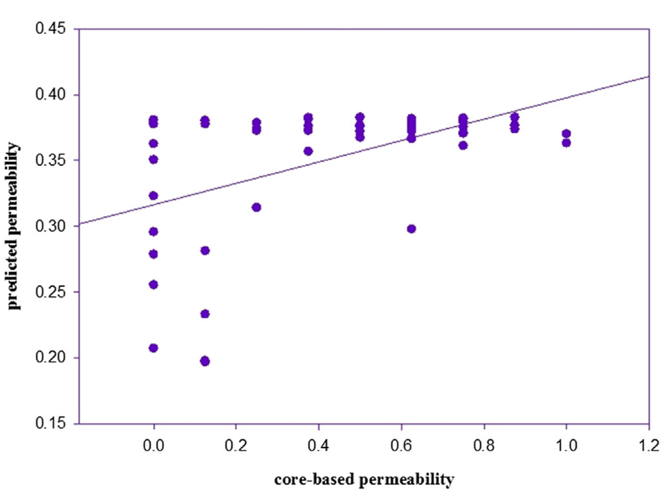

Fig. 5. Scatter plots of predictions made by SVM in dataset 1.

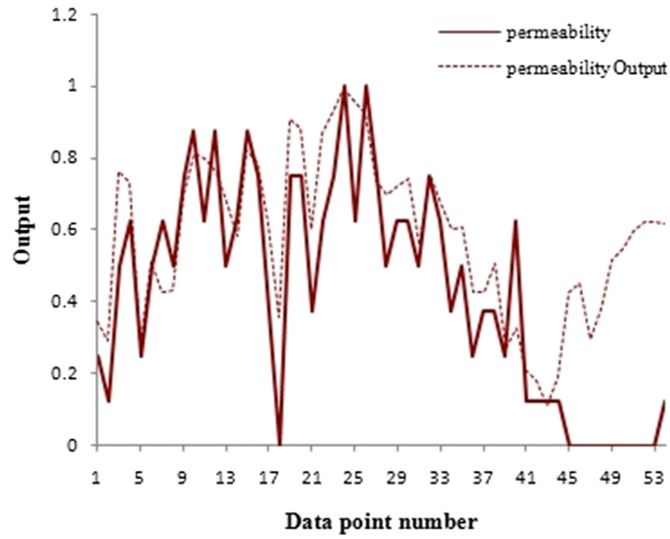

Fig. 6. Comparison of permeability measured of core and predicted by SVM of seen data in dataset 2.

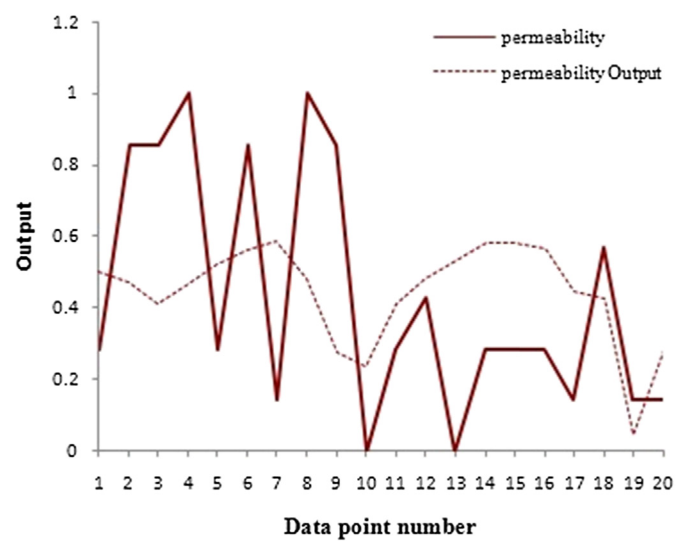

Fig. 7. Comparison of permeability measured of core and predicted by CANFIS of unseen data in dataset 3.

SVM models in estimating previously seen data and Table 6 exhibit results of prediction of permeability from unseen data. In Table 5, CANFIS has the lowest errors in datasets 1, 2 and 3. In dataset 4, SVM is more accurate than two other methods. So, it is obvious that CANFIS is more capable to estimate permeability of previously seen data. In Table 6, CANFIS has the lowest errors in datasets 1, 2 and 4. In datasets 3 and 5, SVM is the best predicting technique. As it can

Table 5
Comparison of AAE and MSE error measures between MLP, CANFIS, and SVM models based on seen data.

Dataset number	MLP		CANFIS		SVM	
	AAE	MSE	AAE	MSE	AAE	MSE
1	0.114	0.102	0.092	0.074	0.106	0.091
2	0.073	0.057	0.059	0.044	0.086	0.067
3	0.103	0.093	0.062	0.049	0.117	0.106
4	0.079	0.055	0.134	0.115	0.089	0.074

Table 6
Comparison of AAE and MSE error measures between MLP, CANFIS, and SVM models based on unseen data.

Dataset number	MLP		CANFIS		SVM	
	AAE	MSE	AAE	MSE	AAE	MSE
1	0.125	0.108	0.089	0.066	0.097	0.085
2	0.147	0.131	0.116	0.097	0.124	0.119
3	0.136	0.129	0.132	0.118	0.136	0.112
4	0.193	0.183	0.128	0.111	0.141	0.123
5	0.129	0.114	0.144	0.138	0.101	0.083

be seen, CANFIS and SVM have similar performances in predicting permeability and exhibit better results than MLP. Also it can be resulted that MLP in comparison with CANFIS and SVM has the poorest capability of predicting permeability.

4. Conclusions

In this research, Multilayer Perceptron Neural Network, Co-Active Neuro-Fuzzy Inference System and Support Vector Machine were employed to predict permeability of Mesaverde tight gas sandstones located in Washakie basin, USA. Capabilities of methods in predicting permeability were evaluated by using 2 different dataset patterns. Accuracy of different methods was compared by using different error statistics. The main conclusions of this study are as follow:

- Multilayer Perceptron Neural Network, Co-Active Neuro-Fuzzy Inference System and Support Vector Machine are appropriate methods for predicting permeability of tight gas reservoir.
- Co-Active Neuro-Fuzzy Inference System is the best estimator of permeability where testing data is the data which was used in training.
- Co-Active Neuro-Fuzzy Inference System and Support Vector Machine have similar performances in predicting permeability of previously unseen data, but Support Vector Machine performs slightly better.
- Multilayer Perceptron Neural Network in presence of small training data cannot work as good as when the training dataset is large.
- The disadvantage of Co-Active Neuro-Fuzzy Inference System is its computation speed. Support Vector Machine in comparison with two other models has the most computation speed.

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