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Support vector regression for prediction of gas reservoirs permeability

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Abstract
Reservoir permeability is a critical parameter for characterization of the hydrocarbon reservoirs. In fact, determination of permeability is a crucial task in reserve estimation, production and development. Traditional methods for permeability prediction are well log and core data analysis which are very expensive and time-consuming. Well log data is an alternative approach for prediction of permeability because they are usually available for all of the wells. Hence, attempts have been made to utilize well log data to predict permeability. However, because of complicate and non-linear relationship of well log and core permeability data, usual statistical and artificial methods are not completely able to provide meaningful results. In this regard, recent works on artificial intelligence have led to the introduction of a robust method generally called support vector machine (SVM). The term "SVM" is divided into two subcategories: support vector classifier (SVC) and support vector regression (SVR). The aim of this paper is to use SVR for predicting the permeability of three gas wells in South Pars filed, Iran. The results show that the overall correlation coefficient (R) between predicted and measured permeability of SVR is 0.97 compared to 0.71 of a developed general regression neural network. In addition, the strength and efficiency of SVR was proved by less time-consuming and better root mean square error in training and testing dataset.

Keywords: *Permeability; hydrocarbon reservoir; well logs; support vector machine; neural network.*

1. Introduction

Reservoir permeability is a critical parameter for characterization of the hydrocarbon reservoirs [1]. In fact, management and development of a reservoir require accurate knowledge of permeability. This petrophysical parameter can be determined by analyzing core, well test or well log data [2, 3]. Although no well log is currently capable of measuring permeability directly, correlating well logs with core permeability at the cored well has become a common practice in the industry [1]. Many empirical equations are available to transform well log data to permeability [2, 4]. These models often require a labor-intensive exercise to adjust constants or exponents or to introduce compensations. Despite these observations, theoretical relations between permeability and porosity have been sought. For example, Kozeny-Carmen theory relates permeability to porosity and the specific area of a porous rock with pores treated as an idealized bundle of capillary tubes. This theory treats the highly complex porous medium in a very simple manner and ignores the influence of conical flow in the constrictions and expansions of flow channels [1].

The statistical approach is comparatively a more versatile approach to the problem of permeability prediction. It makes use of the available core permeability (the dependent variable) and develops functional relationships with the well log data (the independent variables). It, however, requires the assumption and satisfaction of multi-normal behavior and linearity, and hence it must be applied with caution [1].

Alternatively, neural networks have been increasingly applied to predict reservoir properties using well log data [5, 6]. Previous investigations [7-11] have revealed that neural network is a proper tool for identifying the complex relationship among permeability, porosity, fluid saturations, depositional environments, lithology and well log data. However, more studies are still required to improve the obtained results of these research works. In this regard, recent works on the artificial intelligence have resulted in finding a suitable machine learning theory generally called support vector machine (SVM). SVM is divided into two subcategories: support vector classifier (SVC) and support vector regression (SVR). The SVM method (i.e. SVC and SVR) relies on the statistical learning theory which enables learning machines to generalize the unseen data. This method was introduced in the early 1990's as a non-linear solution for classification and regression tasks [12]. This technique has been proven to have superior performances in the variety of problems due to its generalization abilities and robustness against noise and interferences [13, 14]. In general, there are at least three reasons for the success of SVM: its ability to learn well with only a very small number of parameters; its robustness against the error of data; and its computational efficiency compared with several other intelligent computational methods including neural network, fuzzy network, etc [15-17]. The objective of this study is to evaluate the ability of SVR for prediction of permeability in reservoirs with limited data. Kangan and Dallan gas reservoirs in the South Pars field, Iran were selected as the case study in this research work. Furthermore, the results of SVR will be compared with those obtained from a developed general regression neural network (GRNN).

2. Material and Method

2.1. Studied wells and input data

The Iranian South Pars field is the northern extension of Qatar's giant North Field. The field consists of two independent gas-bearing formations called Kangan (Triassic) and Upper Dalan (Permian). Each formation is divided into two different reservoir layers, separated by impermeable barriers. In this field, gas accumulation is mostly limited to the Permian–Triassic stratigraphic units. These units (i.e. Kangan–Dalan Formations) constitute very extensive natural gas reservoirs in this field and Persian Gulf area. They are composed of carbonate–evaporate series and also known as the Khuff Formation [18]. Figure 1 shows the geographical position of South Pars gas field.

As it was mentioned in the introduction section, the main objective of this study is to predict permeability of the gas reservoirs by incorporating well logs of three wells in the southern Pars field. As a matter of fact, the well logs are considered as inputs, whereas the logarithm of horizontal permeability (K_h) is taken as the output of the networks. Available digitized well logs consist of sonic log (DT), gamma ray log (GR), compensated neutron porosity log (NPHI), density log (ROHB), photoelectric factor log (PEF), micro spherical focused resistivity log (MSFL), shallow and deep latero-resistivity logs (LLS and LLD). To show the possible relationship between well logs and permeability, a correlation matrix has been depicted. Table 1 gives the correlation matrix of the well logs and permeability.

Figure1. Geographical position of South Pars gas field

As it is seen in Table 1, there is a high positive relationship among the LKH, DT and NPHI while LKH has a negative correlation with RHOB data. However, other logs cannot establish any good relationships with LKH. In addition, due to both the heterogeneity of the reservoir and complex geology of the area, the location (i.e. X, Y coordinate) and the depth of data (i.e. Z value) are taken into consideration for this study.

In this study, a total number of 175 well logs and core permeability datasets were obtained from 3 wells of Kangan and Dalan gas reservoirs. The database was randomly divided into training and testing subsets using MATLAB multi-purpose commercial software in order to implement the automated Bayesian regularization. This type of regularization can significantly reduce the large amount of error called over-fitting. In view of the requirements of the networks computation algorithms, the data of the input and output

variables were normalized. In this study, normalization of data was carried out using equation (1) and the number of train data (125) and test data (50) were then selected randomly.

$$p_n = 2\frac{p - p_{\min}}{p_{\max} - p_{\min}} - 1 \quad (1)$$

where p_n is the normalized parameter, p denotes the actual parameter, p_{min} represents the minimum of the actual parameters and p_{max} stands for the maximum of the actual parameters. In addition, the cross-validation of the whole training set was used for adjusting the associated parameters of the networks [19].

Table 1. Correlation matrix of the well logs data

	LKH	X	Y	Z	GR	DT	RHOB	NPHI	PEF	MSFL	LLD	LLS
LKH	1											
X	-.112	1										
Y	.110	-.999	1									
Z	.285	.655	-.655	1								
GR	-.015	.219	-.216	.490	1							
DT	.742	-.025	.026	.347	.088	1						
RHOB	-.664	-.011	.010	-.397	-.182	-.915	1					
NPHI	.820	-.110	.107	.240	.167	.746	-.615	1				
PEF	.125	.125	-.119	.361	.210	.350	-.576	.009	1			
MSFL	-.318	.072	-.070	-.164	-.259	-.327	.401	-.318	-.236	1		
LLD	-.106	.107	-.110	.106	-.041	-.153	.169	-.101	-.078	.274	1	
LLS	-.206	.077	-.078	-.023	-.102	-.239	.248	-.203	-.115	.235	.767	1

2.2. Support Vector Machine

Support vector machine (SVM) has been employed for regression estimation, the so called support vector regression (SVR), in which the real value functions are estimated. In this case, the aim of learning process is to find a function f(x) as an approximation of the value y(x) with minimum risk, and only based on the available independent and identically distributed data, i.e.

$$(x_1, y_1), ..., (x_m, y_m) \subseteq (X \subseteq R^n \times Y \subseteq R) \quad (2)$$

In SVR algorithm, the estimation function is determined by a small subset of training samples, namely, support vectors (SVs). Also in this algorithm, a specific loss function called ε-insensitive loss is developed to create a sparseness property for SVR. This function is described as follows

$$\left|y - f(x)\right|_\varepsilon = \begin{cases} 0 & \text{if } \left|y - f(x) \le \varepsilon\right| \\ \left|y - f(x)\right| - \varepsilon & \text{Otherwise} \end{cases} \quad (3)$$

where f(x), which is computed by the SVR, is the estimated value of the y and the corresponding errors being less than ε-boundary (ε-tube) are not penalized (Figure 2).

For developing the regression algorithm, we begin with the linear function estimation. It is clear that every linear function of input vector x has the following representation: [20]

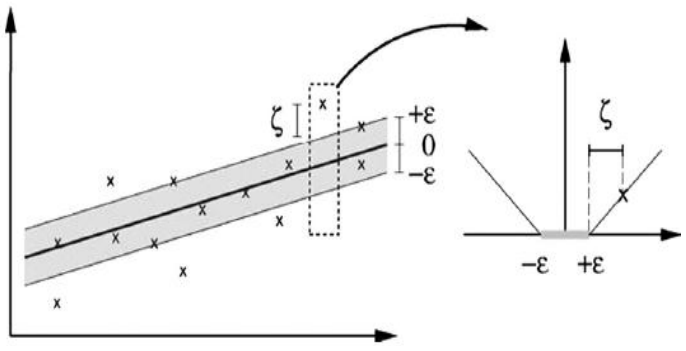

Figure 2. ε-Insensitive loss function [21]

$$f(x) = \langle w.x \rangle + b$$

Where $w, x \in X \subseteq R^n, b \in R$ (4)

It should be noted that angle bracket ($\langle . \rangle$) indicates the inner product of two vectors in Hilbert space (i.e. a space in which inner product of two vectors has a real value, also called inner (or dot) product space). In ε -SVR, the aim is to find a function f(x) that estimates the values of output variables with deviations $\leq \varepsilon$ from the actual training data. The ε -values control the complexity of the approximating functions where small values tend to penalize large portion of the training data leading to tight approximating models and large values tend to free data from penalization leading to loose approximating models. Therefore, the proper choice of e-value is critical for the generalization of regression models.

To find f(x), one should minimize the regulated risk functional (R_{reg}) (instead of just empirical risk functional which is used in traditional learning algorithms such as ANN) defined as follows [22]:

$$R_{reg}[f] = \frac{1}{2}\|w\|^2 + C.R_{emp}^{\varepsilon}[f] \qquad (5)$$

$$\text{where } R_{emp}^{\varepsilon}[f] = \frac{1}{m}\sum_{i=1}^{m}|y_i - f(x_i)|_{\varepsilon}$$

The R_{emp} is the empirical error over training data which is defined in ε-insensitive loss function framework. The regularization coefficient *C* in the Eq. (5) is an indicator of the complexity of function *f* and penalizes the error by setting the tradeoff between training error minimization and model complexity. Briefly, the minimization of the R_{reg} illustrates the principle idea of the structural risk minimization theory which states that for achieving the minimum risk, simultaneous control of the complexity of the model and the error owing to training data is essential. This idea improves the generalization of the SVR.

It has been proven that minimizing the Eq. (5) is equivalent to the following convex constrained quadratic optimization problem [23]:

$$L(w,\xi,\xi') = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}(\xi_i + \xi_i') \qquad (6)$$

$$Subject\ to \begin{cases} y_i - w^T.x - b \leq \xi_i + \varepsilon \\ w^T.x + b - y_i \leq \xi_i' + \varepsilon \\ \xi_i, \xi_i', x_i \geq 0 \end{cases}$$

where ξ_i and ξ_i' are slack variables introduced to satisfy constraints on the function. Therefore, SVR fits a function to the given data by not only minimizing the training error but also by penalizing complex fitting functions. The first term of Eq. (6) is the Vapnik– Chervonenkis (VC) confidence interval whereas the second one is the empirical risk. Both terms limit the upper bound of the generalization error rather than limit the training error. This means that SVR strikes a balance between the empirical error and VC-confidence interval which leads to improved generalization performance than neural network models [24]. In Eq. (6), C tries to ensure the margin ε is maximized and error of the classification ξ is minimized. According to Eq. (6), any error smaller than ε does not require a nonzero ξ_i or ξ_i', and does not enter the objective function [25].

By introducing Lagrange multipliers (α and α') and allowing for $C > 0$, $\varepsilon > 0$ chosen a priori, the equation of an optimum hyper plane is achieved by maximizing the following relations:

$$L(\alpha,\alpha') = \frac{1}{2}\sum_{i=1}^{N}\sum_{i=1}^{N}(\alpha_i - \alpha_i')x_i'x_i(\alpha_i - \alpha_i') + \sum_{i=1}^{N}((\alpha_i - \alpha_i')y_i - (\alpha_i + \alpha_i')\varepsilon) \qquad (7)$$

$$Subject\ to\ 0 \leq (\alpha_i - \alpha_i') \leq C \qquad (8)$$

where, x_i only appears inside an inner product. To get a potentially better representation of the data in non-linear case, the data points can be mapped into an alternative space, generally called feature space (a pre-Hilbert or inner product space) through a replacement:

$$x_i.x_j \rightarrow \varphi(x_i).\varphi(x_j) \qquad (9)$$

The functional form of the mapping $\varphi(x_i)$ does not need to be known since it is implicitly defined by the choice of kernel: $k(x_i, x_j) = \varphi(x_i).\varphi(x_j)$ or inner product in Hilbert space. With a suitable choice of kernel, the data can become separable in feature space while the original input space is still non-linear. Thus, whereas data for n-parity or the two-spiral problem is non-separable by a hyper plane in input space, it can be separated in the feature space by the proper kernels [26, 27]. Table 2 gives some of the common kernels.

Then, the nonlinear regression estimate takes the following form:

$$y_i = \sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i - \alpha_i')\phi(x_i)^T\phi(x_j) + b = \sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i - \alpha_i')K(x_i, x_j) + b \qquad (10)$$

where b is computed using the fact that constrains of equation (6) becomes $\xi_i = 0$ if $0<\alpha_i<C$, and $\xi_i' = 0$ if $0 < \alpha_i' < C$ [28].

Table 2. Polynomial, Normalized Polynomial, Radial Basis Function (Gaussian) and Pearson Universal (PUK) Kernels [16]

Kernel Function	Type of Classifier
$K(x_i,x_j)=(x_i^{\mathrm{T}}x_j+1)^{\rho}$	Complete polynomial of degree ρ
$K(x_i,x_j)=\dfrac{(x_i^{T}x_j+1)^{\rho}}{\sqrt{(x_i^{T}x_j)-(y_i^{T}y_j)}}$	Normalized polynomial kernel of degree ρ
$K(x_i,x_j)=\exp\left[\left\|x_i-x_j\right\|^2/2\sigma^2\right]$	Gaussian (RBF) with parameters σ (sigma) control the half-width of the curve fitting peak
$K(x_i,x_j)=\dfrac{1}{\left[1+\left(\dfrac{\left(2\sqrt{\left\|x_i-x_j\right\|^2}\sqrt{2^{1/\omega}-1}\right)}{\sigma}\right)^2\right]^{\omega}}$	Pearson VII Universal Kernel (PUK) with two parameters of σ (sigma) and ω (omega) which control the Pearson width and the tailing factor of the curve fitting peak

There are a quite number of algorithms for SVR training, and Sequential Minimum Optimization (SMO) is an efficient one for this purpose [29]. It is a simple algorithm which can quickly solve the SVR quadratic programming problem without any extra matrix storage and is exempt from using any numerical quadratic programming optimization steps. SMO decomposes the overall quadratic programming problem into sub-problems of quadratic programming by using Osuna's theorem to ensure convergence. There are two specific components in the structure of SMO: an analytic method for solving the two Lagrange multipliers; and a heuristic one for choosing multipliers in optimization step [30].

The advantage of SMO lies on the fact that solving for two Lagrange multipliers can be done analytically. Hence, numerical quadratic programming optimization can be avoided completely [30]. In addition, SMO requires no extra matrix storage. Thus, very large SVR training problems can fit inside the memory of an ordinary personal computer or workstation. In this study, SMO algorithm is used for both optimizing the structure of SVR and helping to predict the permeability in reasonable running time.

2.3. General regression neural network

General Regression Neural Network (GRNN) has been proposed by Specht (1991). GRNN is a type of supervised network and also trains quickly on sparse data sets but, rather than categorizing it. This algorithm provides smooth transitions from one observed value to another even with sparse data in a multidimensional measurement space. GRNN can be thought as a normalized Radial Basis Functions (RBF) network in which there is a hidden unit centered at every training case. These RBF units are usually probability density functions such as the Gaussian. The only weights that need to be learned are the widths of the RBF units. These widths are called "smoothing parameters". The regression of a dependent variable, Y, on an independent variable, X, is the computation of the most probable value of Y for each value of X based on a finite number of possibly noisy measurements of X and the associated values of Y.

This method does not need to assume a specific functional form. A Euclidean distance (Di^2) is estimated between an input vector and the weights, which are then rescaled by the spreading factor. The radial basis output is then the exponential of the negatively weighted distance. The GRNN equation can be written as:

$$D_i^2=(X-X^i)^T(X-X^i) \qquad (11)$$

$$Y(X)=\frac{\sum_{i=1}^{n}Y_i\exp(-\frac{D_i^2}{2\sigma^2})}{\sum_{i=1}^{n}\exp(-\frac{D_i^2}{2\sigma^2})}$$

where, σ is the smoothing factor (SF) and T stands for transpose notation.

In this theory, the optimum smoothing factor is determined after several runs according to the mean squared error of the estimate, which must be kept at minimum. This process is referred to as the training of the network. If a number of iterations pass with no improvement in the mean squared error, that smoothing factor is determined as the optimum one for that data set. While applying the network to a new set of data, increasing the smoothing factor would result in decreasing the range of output values [31]. The smoothing factor must be greater than 0 and can usually range from 0.1 to 1 with good results.

3. Results

3.1. Prediction of permeability using SVR

As it was mentioned, the performance of SVR depends mostly on the choice of kernel function and which is in a sense equivalent to the choice of the ANN structure. In this regard, despite the obtained results of previous research works [32, 33], indicating the Gaussian radial basis function as a superior kernel, optimal kernel was selected based upon the root mean square error (RMSE) of SVR during the training process. Obtained results of this study are shown in Figure 3.

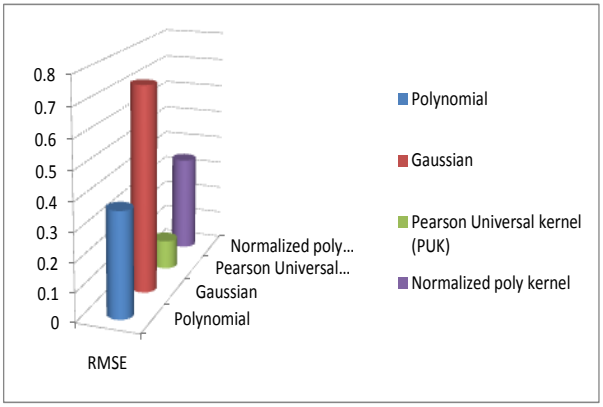

Figure 3. Different kernels with their relative RMS error during the training process

As it is depicted in Figure 3, different kernels were compared to each other. The obtained results seem to be logical because polynomial and normalized polynomial kernels are usually used in the simple nonlinear systems and there were the error of 0.36 and 0.33 for these kernels respectively. There is also an unexpected result for the performance of Gaussian kernel because the RMSE of this kernel was around 0.68. As shown in Figure 3, Pearson Universal Kernel (PUK) is the best one for the estimation of permeability with an error of 0.06.

Moreover, for implementation of the SVR, the appropriate values of optimal parameters C (trade-off parameter), σ and ω (parameters of Pearson Universal kernel) need to be determined prior to building the model. For managing this issue, among all model selection tools, cross-validation techniques can be rigorous for adjusting associated parameters of SVR because they make no biased assumptions about the data and noise distribution. The Leave One Out (LOO) is a cross validation procedure consisting of removing one example from the training set, constructing the decision function on the basis only of the remaining training data and then testing on the removed example [19]. In this fashion, one tests all examples of the training data and measures the fraction of errors over the total number of training examples. To obtain the optimal value of σ, the SVR with different σs was trained, the σ varying from 0.01 to 0.2, every 0.01. At last, the optimal σ was found as 0.13. In order to find an optimal ε and ω, the RMSE on different εs and ωs were calculated. The optimal ε and ω were found as 0.08 and 0.23 respectively. Figure 4 shows the LOO cross validation step used for selecting the best values of σ, ε and ω.

In the next stage, regarding to many combinations of the input variables, a set of nine input parameters (i.e. X, Y, Z, DT, RHOB, NPHI, GR, PEF, MSFL) were selected based on the least RMSE and the highest R values of SVR model during the training and testing process (Table 3).

Ultimately, a Matlab software code (i.e. M.file) was developed and used to evaluate the performance of SVR using the available (measured) permeability data. Table 4 reports the measured and predicted permeability for testing data set. As it is seen in Table 4, there is an acceptable agreement between the predicted and measured permeability. Figure 5 shows the performance of SVR in prediction process.

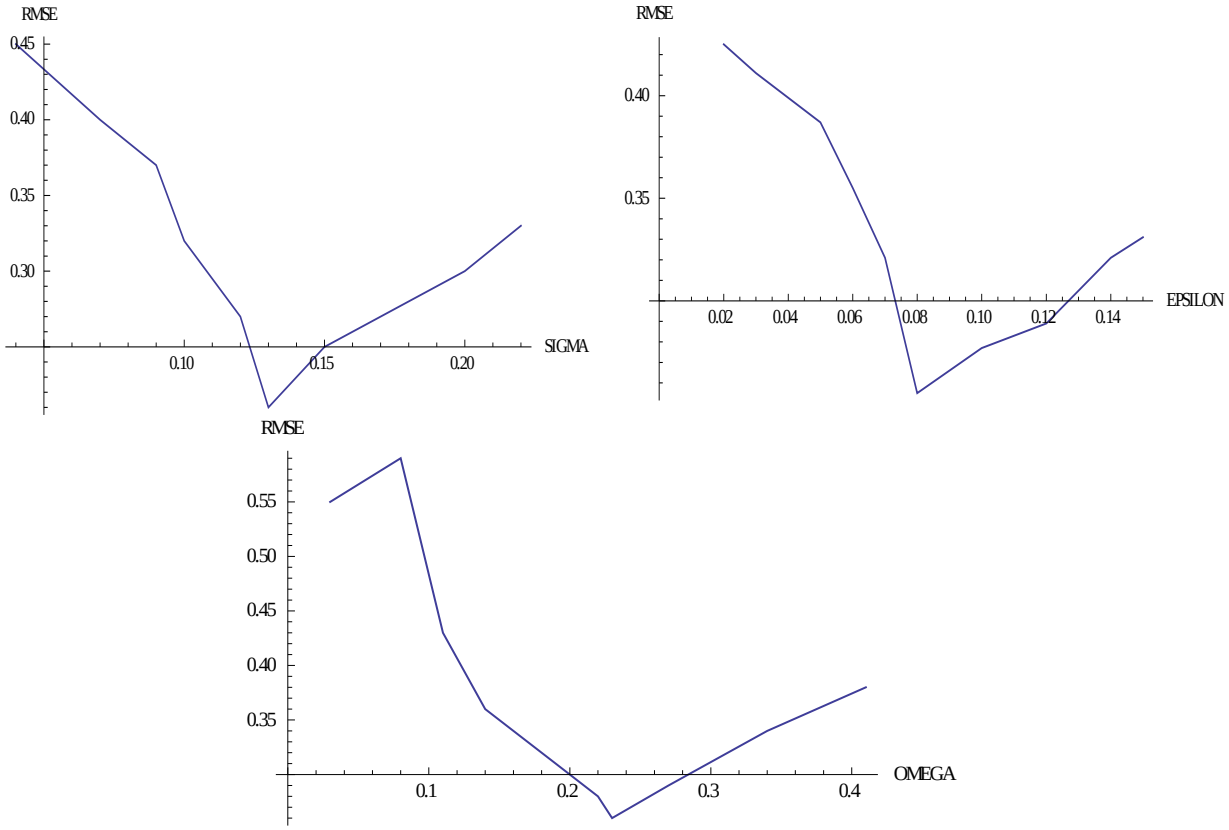

Figure 4. RMS error versus σ (left), versus ε (right) and versus ω (bottom) in LOO cross-validation step

3.2. Prediction of permeability using general regression neural network

In order to check the accuracy of SVR in prediction of permeability, obtained results of SVR are compared with that of the GRNN. This network was already developed by my co-author [34] and its efficiency in the prediction of permeability was successfully tested. The structure of the GRNN model includes one input layer consisting 9 neurons, one hidden layer of radial basis function comprising 174 neurons and an output layer containing only one neuron. Multiple layers of neurons with nonlinear transfer functions allowed the network to learn nonlinear and linear relationships between the input and output vectors.

Smooth factor (SF) is the most important feature in the structure of GRNN. This parameter was determined regarding to the RMSE of dataset. Finally, the optimum value of the smooth factor was found as 0.23. Figure 6 shows the process of finding the best SF for the training set. Table 5 represents the performance of GRNN in prediction of permeability while the training and testing datasets were the same as those of the SVR. As it is seen in Table 5, the capability of GRNN in prediction of permeability is not as good as that of the SVR (see Table 4). In fact, there is a correlation coefficient of 0.711 between the measured and predicted permeability of GRNN. Figure 7 clearly represents the efficiency of GRNN in prediction of permeability.

Table 3. The results and performance of SVR with different input parameters

Input variables	R (Train)	R(Test)	RMSE (Train)	RMSE (Test)
DT, RHOB, NPHI	0.935	0.920	0.67	0.81
DT, RHOB, NPHI, MSFL	0.952	0.937	0.55	0.64
X, Y, Z, DT, RHOB, NPHI	0.978	0.950	0.33	0.47
X, Y, Z, DT, RHOB, NPHI, GR, PEF, MSFL	0.99	0.97	0. 06	0.08

Table 4. Comparison between the predicted results of SVR with those of the measured data

Sample. No	Measured Permeability (md)	Predicted permeability by SVR (md)	Sample. No	Measured Permeability(md)	Predicted permeability by SVR(md)
1	2.27	2.11	26	1.6	1.51
2	1.9	1.8	27	1.8	1.71
3	1.7	1.65	28	1.9	1.71
4	1.6	1.49	29	2.3	2.15
5	1.3	1.25	30	2.39	2.49
6	1.5	1.35	31	1.82	1.92
7	1.3	1.19	32	1.823	1.75
8	1.3	1.38	33	1.79	1.63
9	1.21	1.11	34	2.23	2.47
10	1.09	1.1	35	2	1.91
11	0.86	0.78	36	2.301	2.271
12	0.87	0.73	37	2.301	2.286
13	1.24	1.35	38	1.79	1.89
14	0.87	0.95	39	2.22	2.46
15	0.717	0.743	40	1.88	1.68
16	0.83	0.69	41	1.95	1.86
17	0.84	0.99	42	1.9	1.97
18	0.51	0.43	43	2.03	2.12
19	0.191	0.201	44	2.22	2.06
20	0.86	0.83	45	2.15	2.11
21	0.98	0.92	46	2.15	2.24
22	1.09	0.99	47	2.22	2.16
23	1.4	1.2	48	2.301	2.309
24	1.5	1.57	49	2.522	2.678
25	1.4	1.39	50	2.522	2.453

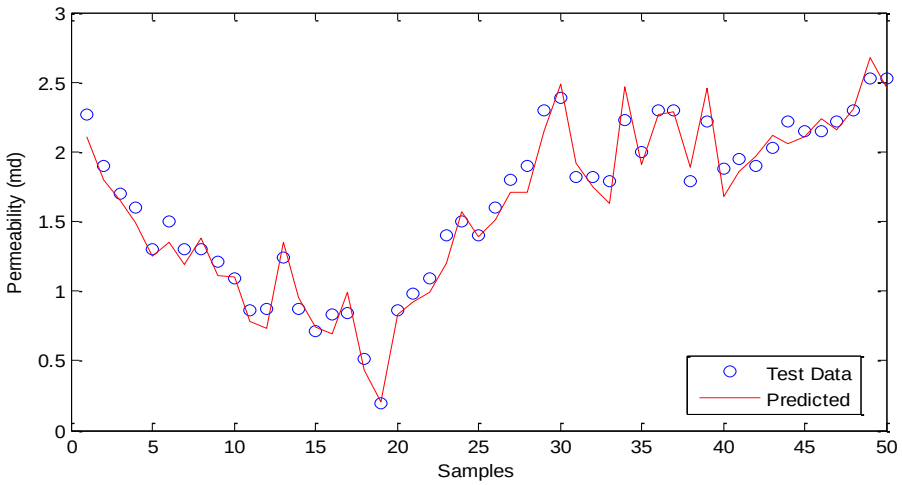

Figure 5. Performance of SVR in predicting permeability

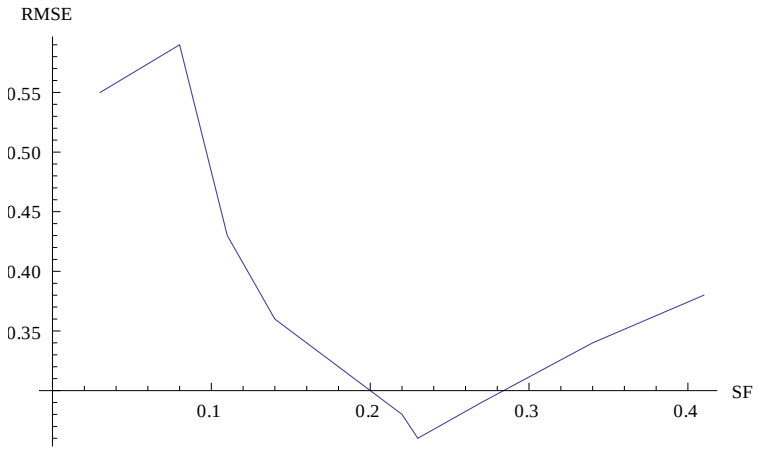

Figure 6. SF versus RMSE on LOO cross-validation

Table 5. Comparison of the measured with predicted permeability in testing dataset

Sampling No	Measured Permeability (md)	Predicted Permeability by GRNN(md)	Sampling No	Measured Permeability(md)	Predicted Permeability by GRNN(md)
1	2.27	1.8	26	1.4	1.6
2	1.9	1.7	27	1.6	1.5
3	1.7	1.6	28	1.8	1.2
4	1.6	1.4	29	1.9	1.3
5	1.3	1.1	30	2.3	1.53
6	1.5	1.4	31	2.39	1.79
7	1.3	1.01	32	1.82	1.71
8	1.3	1.01	33	1.823	1.906
9	1.21	1.24	34	1.79	1.704
10	1.09	1.11	35	2.23	1.74
11	0.86	1.14	36	2	1.9
12	0.87	1.22	37	2.301	1.51
13	1.24	0.931	38	2.301	2.021
14	0.87	1.14	39	1.79	1.93
15	0.717	0.481	40	2.22	1.84
16	0.83	0.701	41	1.88	2
17	0.84	0.55	42	1.95	1.8
18	0.51	0.97	43	1.9	1.8
19	0.191	0.298	44	2.03	2.04
20	0.86	1.03	45	2.22	1.9
21	0.98	1.44	46	2.15	2.08
22	1.09	1.29	47	2.15	1.9
23	1.4	1.9	48	2.22	2.24
24	1.5	1.9	49	2.301	2.073
25	1.4	1.6	50	2.522	2

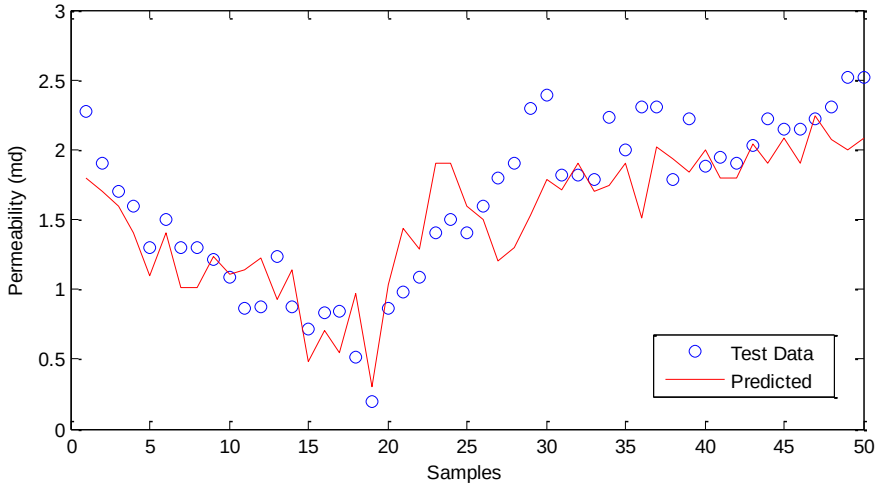

Figure 7. Performance of GRNN in prediction of permeability

4. Discussion

In this research work, the performance of SVR algorithm was demonstrated in prediction of permeability. In this regard, two Matlab software codes (i.e. M.files) were developed and utilized for interrogating the performance of SVR with the best performed work of GRNN model. When we compared the obtained results of SVR with those of the GRNN model, the SVR presented better overall performance over GRNN approach in terms of RMSE and correlation coefficient (R) during both training and testing process (Table 6).

Table 6. Assessing the performed work of the SVR and GRNN

Model	R (Train)	R(Test)	RMSE (Train)	RMSE (Test)
GRNN	0.996	0.711	0.06	0.22
SVR	0.998	0.97	0.06	0.08

Table 6 shows the estimation capability of SVR and GRNN models in the independent training and test phases. According to this Table, the RMSE of SVR model is smaller than that of the GRNN. Figure 8 shows the scatter plots of measured and predicted permeability of each method in test data set.

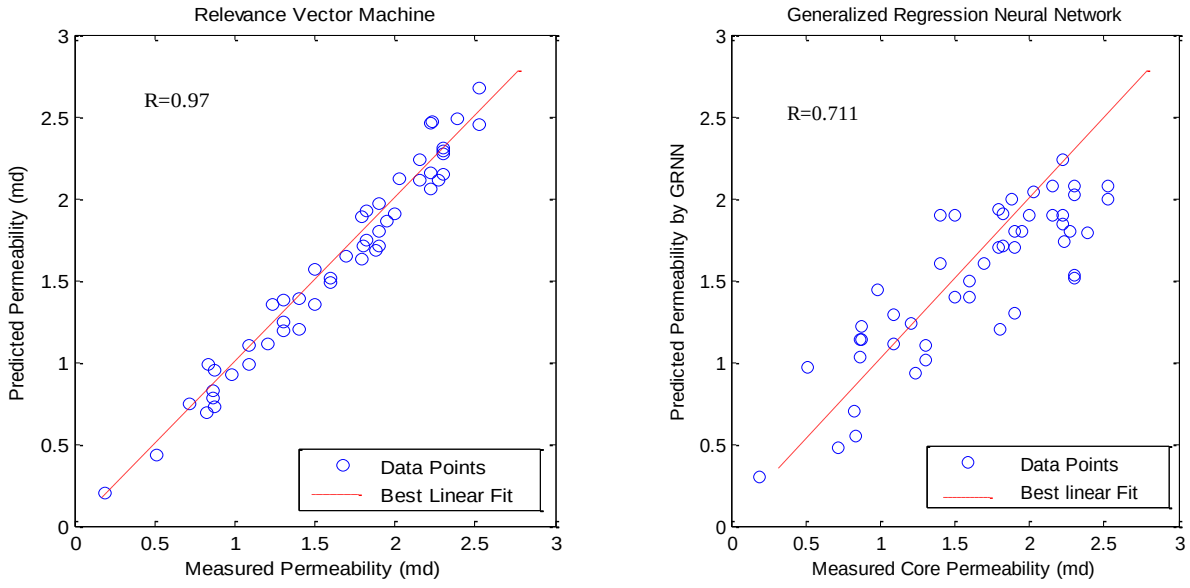

Figure 8. Relationship between the measured and predicted permeability obtained by SVR and GRNN methods for test dataset

The plots indicate that an acceptable prediction (i.e. R=0.97) was obtained through the SVR modeling. In addition, the SVR consumes considerably less time for prediction compared to that of the GRNN. All of these expressions introduce the SVR as a suitable algorithm for the prediction of permeability.

5. Conclusions

In this research work, we have shown the application of SVR compared with GRNN model for prediction of permeability of three gas wells in the Kangan and Dalan reservoir of South Pars Field, based on the digital well log data. Although both methods are data-driven models, it has been found that the SVR makes the running time considerably faster with the higher accuracy. In terms of accuracy, the SVR technique resulted in a RMSE reduction relative to that of the GRNN model (Table 6). Regarding the running time, SVR requires a small fraction of the computational time used by GRNN, an important factor in choosing an appropriate and high-performance data-driven model.

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