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A hybrid PSO-SVM-based model for determination of oil recovery factor in the low-permeability reservoir

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ABSTRACT

Oil recovery factor is one of the most important parameters in the development process of oil reservoir, especially in the low-permeability reservoir. In general, the determination of recovery factor can be obtained either experimentally or numerically. Experimental method is often time-consuming and expensive, while numerical method has been always confined to narrow range of application or relatively large error. Recently, an intelligent method has been proven as an efficient tool to model the complex and nonlinear phenomena. In this work, an intelligent model based on support vector machine in combination with the particle swarm optimization (PSO-SVM) technique was established to predict oil recovery factor in the low-permeability reservoir. Input variables of the proposed PSO-SVM model with the aid of a grey correlation analysis method are permeability, well spacing density, production-injection well ratio, porosity, effective thickness, crude oil viscosity and output parameter is oil recovery factor of low-permeability reservoir. The accuracy and reliability of the proposed model were evaluated through 34 data sets collected in the open literature and compared with PSO-BP neural network, empirical method from Oil and Gas Company. The results indicated that the PSO-SVM model gives the best results with average absolute relative deviation (*AARD*) of 3.79%, while AARDs for the PSO-BP neural network and empirical method are 9.18% and 10.0%, respectively. Furthermore, outlier detection was used on the basis of whole data sets to definite the valid domains of PSO-SVM and PSO-BP models by detecting the probable doubtful recovery factor data in the low-permeability reservoir.

1. Introduction

It is well acknowledged that the oil recovery factor has been seen as one of the most important parameters in the process of reservoir development. The assessment of whether the oil field is fully exploited or economic recovery is maximized heavily depends on the accuracy of estimating oil recovery factor, especially for the low-permeability reservoir. Generally speaking, the determination of recovery factor can be obtained either experimentally or numerically, and these approaches can be divided into three major groups: water/oil displacement mechanism [1], mathematical statistics theory [2–6] and oil field development dynamics [7,8]. However, the study on recovery factor estimation for the low-permeability reservoir is a hot and difficult issue because of the complex non-linear fluid flow through porous medium, such as non-Darcy flow, starting pressure gradient, stress sensitivity and fluid-solid coupling, which indicate that the conventional methods are not suitable for determination of the recovery factor in low-permeability reservoirs. As early as 1997, Wang et al. [9] proposed five different methods for calculating the recovery factor of low-

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permeability reservoir, but different methods were only applied to different stages of oil field development. Niu et al. [10] (2006) provided a method to estimate the water flooding recovery factor in low-permeability reservoirs after analysis of the impact of the well pattern factor, the oil displacement efficiency and the sweep coefficient on recovery factor through several empirical formulas. Jiang et al. [11] (2010) derived an equation to calculate recovery factor by combining nonlinear unsteady seepage theory with the determination of the radius of oil leakage. However, this equation can only be used for the elastic stage of low-permeability reservoirs. Recently, the empirical formulas [12,13] for calculating the recovery factor of low-permeability reservoir were given by using multiple regression theory. Besides less number of parameters, the formula was also confined to its narrow application and produced lower accuracy.

In recent years, the decrease of the recovery factor in oil reservoir and the fluctuation of oil prices have resulted in paying much more attention to enhanced oil recovery (EOR). Therefore, intelligent algorithms, especially integrating artificial neural network (ANN) and support vector regression optimized by particle swarm optimization (PSO) or genetic algorithm (GA) were widely used in petroleum engineering for modeling the complex and nonlinear phenomena, including well-test analysis [14,15], well-log interpretation [16–18], reservoir characterization [19–23], PVT [24–27], permeability of crude oils [28–30] and asphaltene precipitation [31–33]. In particular, Ahmadi et al. [34] proposed a novel and hybrid PSO-ANN-based model to predict the productivity of horizontal wells under different conditions. The results of the proposed model have closer match to the real data collected from the open literature. Afterwards, a least square support vector machine (LS-SVM) [35] was integrated with genetic algorithm (GA) and imperialist competitive algorithm to estimate the minimum miscibility pressure (MMP). The results from HGAPSO-LSSVM model have been compared with other intelligent approaches and the performances of both implemented solutions certify great potential in prediction of the MMP. However, the data points of HGAPSO-LSSVM model were lack of diversity and universality. For this reason, Bian et al. [36] collected as many as 150 data sets from the open literature and combined a support vector regression model with genetic algorithm (GA-SVR) to predict pure and impure CO_2-crude oil MMP. The results showed that the proposed model is in excellent agreement with experimental data in prediction of pure and impure CO_2-oil MMP. Also, the swarm intelligence and artificial neural network (ANN) models [37] were provided for determining the dew point pressure. The models can aid in better understanding reservoir fluid behavior through reservoir simulation scenarios. Meanwhile, Mohammadet al. [38] also provided a novel method to predict dew point pressure in gas condensate reservoirs. The proposed intelligent model can be regarded as a feasible method to calculate the dew point pressure of condensate gas reservoirs when the required real data cannot be acquired. In 2017, artificial neural network and piecewise linear (PWL) algorithm [39] were integrated to simulate four datasets of the carbon capture process system. The results revealed that implication of PWL-ANN model in carbon capture process system got more reliable accuracy.

In this work, a regression model based on support vector machine in combination with the particle swarm optimization (PSO-SVM) technique was proposed to predict the recovery factor of low-permeability reservoir. The correlation coefficients of each factor were calculated by using a grey correlation analysis method to obtain the key influencing factors for recovery factor of low-permeability reservoir. Moreover, a PSO-BP neural network model was also presented to estimate the recovery factor. The accuracy of the proposed hybrid PSO-SVM-based model was compared with PSO-BP neural network and empirical method from Oil and Gas Company to demonstrate the validity of the presented PSO-SVM-based method. In addition, outlier diagnosis was performed for detection of the probable doubtful recovery factor in low-permeability reservoir.

2. Methodology

2.1. Support vector machine regression

Support vector machine (SVM) based on statistical-learning theory is an innovative machine learning algorithm employed by Vapnik et al. [40] in 1995 and widely used for classification and regression [41–43]. The SVM algorithm follows the structural-risk-minimization principle, which has the advantages of strong theory and good generalization ability. This new algorithm can well solve the practical problem of small samples with the high dimension and nonlinearity, effectively avoid local optimum, poor generalization ability and the difficulty of selecting structural parameters, and also overcome the disadvantages of conventional BP neural network.

When it comes to the nonlinear SVM regression, the basic idea is to transform the nonlinear regression problem of low dimensional space into linear regression of high dimensional feature space by a nonlinear mapping (particularly radial basis function). The specific algorithm of SVM's dual optimization problem is as follows:

$$max\left[-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\left(\alpha_i-\alpha_i^*\right)\left(\alpha_j-\alpha_j^*\right)\varphi\left(x_i,x_j\right)+\sum_{i=1}^{n}\alpha_i(\varepsilon-y_i)+\sum_{i=1}^{n}\alpha_i^*(\varepsilon+y_i)\right] \tag{1}$$

$$s.t.\begin{cases}\sum\limits_{i=1}^{n}\left(\alpha_i-\alpha_i^*\right)=0\\ \alpha_i,\alpha_i^*\in[0,C](i=1,2,\ldots,n)\end{cases} \tag{2}$$

where n, (x_i, j_{ob}), (a, a_{im}^*), ε, C, and $\varphi(x_i, x_j)$ the Lagrange multiplier pair corresponding to each sample, the system error, the penalty factor, and kernel function, respectively.

Four types of common kernel functions are provided including Linear, Polynomial, Basis Function Radial (RBF) and Sigmoid. Among them, the RBF can often get good performance and more application. The RBF is given by Eq. (3):

$$\varphi\left(x_i,x_j\right)=\exp\left(-\gamma\|x_i-x\|_j^2\right),(\gamma>0) \tag{3}$$

Calculation b:

$$b=\begin{cases}y_i+\varepsilon-\sum\limits_{i,j=1}^{m}\left(\alpha_i-\alpha_i^*\right)\varphi\left(x_i,x_j\right)\alpha_i\in(0,C)\\ y_i-\varepsilon-\sum\limits_{i,j=1}^{m}\left(\alpha_i-\alpha_i^*\right)\varphi\left(x_i,x_j\right)\alpha_i^*\in(0,C)\end{cases} \tag{4}$$

where m is the number of support vectors.

A new hyper plane f was generated through the optimization training:

$$f(x) = \sum_{i,j=1}^{n} (\alpha_i - \alpha_i^*) \varphi(x_i, x_j) + b \tag{5}$$

With

$$x_i, x_j \in R^n, b \in R \tag{6}$$

2.2. Particle swarm optimization technique

The particle swarm optimization (PSO) algorithm, firstly proposed by Eberhart and Kennedy [44] in the 1995, is an optimization algorithm inspired by the social behavior of birds and used to solve all kinds of optimization problems. The most fundamental idea is that each bird in the flocks is considered as one of the particles, then each particle represents a potential solution to the optimization problem and also corresponds to an adaptive function to determine the degree of particle movement. The speed of particles determines the direction and distance of particle movement, while the velocity of the particle is adjusted dynamically with the movement of its own and other particles so as to realize optimization of the individual in the solution space of optimization. In general, the PSO is encoded with simple real-value encryption and less adjustment parameters, which is able to show good performance in solving nonlinear multi-objective constrained optimization problems. Some researchers [45–47] found that PSO-based ANN has a better training performance, faster convergence rate, as well as a better predicting ability than BP-based ANN.

As for the PSO algorithm, each individual particle of the swarm is considered as a vector x_i that contains the required parameters in order to optimize the objective function. The particle dimension is the number of parameters and the particle length is seen as the dimension of this function. Their position X_i^k and velocity V_i^k are randomly initialized in a space of possible solutions. The objective function value is then calculated for each particle. Meanwhile, the velocities and positions are updated based on these values. The algorithm updates the positions and velocities of the particles by following the equations:

$$V_i^{k+1} = \omega V_i^k + \varphi_1 \left(g^k - X_i^k \right) + \varphi_2 \left(I_i^k - X_i^k \right) \tag{7}$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{8}$$

where ω is the constant inertia weight, φ_1 and φ_2 are determined by $c_1 r_1$ and $c_2 r_2$, respectively.

3. Design, development and test of SVM modeling

In this part, three practical steps would be considered with the aim to find the optimal SVM model for prediction of oil recovery factor in low-permeability reservoirs. Moreover, the accuracy and reliability of the proposed model were evaluated through 34 data sets collected in the open literature.

3.1. Input and output variables

The estimation of oil recovery factor of low-permeability reservoirs is a relatively complex process which is influenced by many factors, mainly including reservoir physical properties, fluid properties and development dynamics. Nevertheless, it is extremely difficult to take into account all the factors simultaneously. Therefore, it is necessary to find out major affecting factor considered as a high priority. According to previous studies [12,13,48–50] and the available data [51], a grey relational analysis [52,53] is adopted to screen out the major factors whose correlation degrees are more than 0.65, as shown in Fig. 1. The correlation degrees less than 0.65 are not shown in Fig. 1. As can be seen in Fig. 1, the factors of the first three correlation degrees are permeability (K), well spacing density (S) and production-injection well ratio (γ). The order of the latter three is porosity (φ), effective thickness (H) and viscosity of crude oil (μ), respectively. K, named the geological factor, is the most important factor affecting recovery factor of low-permeability reservoir. S and γ are engineering factors and the practical development operation can be available from the engineering factor, which can effectively improve the recovery of low-permeability reservoir. Certainly, φ, H and μ are all geological factors.

It was surprising that $AARD$ and R^2 of the PSO-SVM model is 9.3% and 0.843 if the first five factors were used as input parameters, while those for the six factors are 3.79% and 0.997. The reason may be that the influence of fluid viscosity on recovery factor of low-permeability reservoir cannot be neglected. However, when water content ratio was added to input parameters considered as the seventh factor with correlation degree 0.483, the performance of the proposed PSO-SVM model becomes very poor and the error ($AARD = 15.6\%$) is also relatively larger than that with only six factors.

Based on the above analysis, we choose the first six factors (K, S, γ, φ, H and μ) as input parameters. The recovery factor (E_R) was set as output parameter. Therefore, a model on the basis of PSO and SVM was established to predict the recovery factor of low-permeability reservoir.

3.2. Selection of learning samples

Data selection of the PSO-SVM model is one of the most important stages in order to increase the accuracy of model prediction by obtaining a good training set. Due to the few number of reported recovery factors in low-permeability reservoirs from open literature, the data in this work were collected from ref.50 and ref. 51. 34 different data series belonging to 12 different geographic and oil regions from Jilin Oilfield were used to make the samples representative and diverse. The range of the sample data should be wide and the specific data are shown in Table 1. These data were randomly divided into two sets including training set (25 of all data) and testing set (9 of all data).

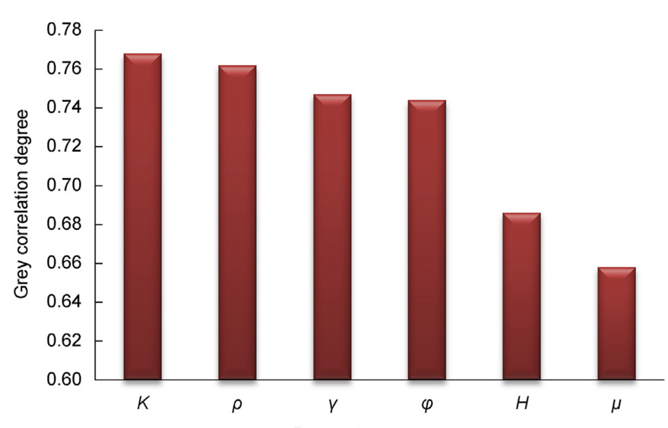

Fig. 1. Grey correlation degree of each parameter.

Table 1
The range of training and learning samples for the proposed SVM model.

Variable	K/mD	Φ/%	μ/mPa s	H/m	ρ/well km^{-2}	γ	E_R/%
Range	0.5–39	10.5–23.3	3.9–12.7	2.8–23.5	6.2–35.3	1.5–10	15–40.5

Sample data were normalized and anti-normalized by employing "mapminmax" function to improve the accuracy of prediction. The mapping used by the "mapminmax" function is given as follows:

$$\tilde{x} = 2\frac{x - x_{\min}}{x_{\max} - x_{\min}} - 1, \quad (\tilde{x} \in [-1, 1]) \tag{9}$$

3.3. Model establishment and parameters optimization

In this work, the MATLAB software and LIBSVM-3.1-Faruto Ultimate 3.1 Mode toolbox (by faruto) [54] were used to establish the PSO-SVM model and then train it. The ε-SVR regression model during training was chosen as the kernel function (Usually RBF kernel function) to obtain the good performance. The performance of ε-SVR regression model strongly depends on the selection of ε-SVR regression parameters, mainly including: penalty factor C and kernel function parameter g and the allowable error ε. Therefore, the key process of model establishment is the optimization of parameter (C, g and ε) [55]. Currently, the methods commonly used to optimize parameters of ε-SVR regression model are as follows: empirical method, grid search method, Bayesian framework method, genetic algorithm and so on. But in the present work, a novel intelligent optimization algorithm-Particle Swarm Optimization (PSO) algorithm was employed in the process of parameter optimization. The flowchart of the PSO algorithm is shown in Fig. 2.

In the process of parameter optimization, the penalty factor C is the most important parameter which greatly affects the accuracy of ε-SVR regression model. If C value is too large, training samples have the very high fitting accuracy, but the generalization ability of the regression model is very poor, named too learning phenomenon; if the C value is too small, seeking optimal process takes a long time and the search is not complete, so the fitting results of training samples are also very poor and the ability of the model generalization is very low. In other words, there is a serious phenomenon of learning. It was found that the C value should be chosen as small as possible (usually between 0 and 100) to ensure the good generalization and accuracy of ε-SVR regression model. Thus, for PSO-SVM model, the global optimal penalty factor $C = 11.01$, $g = 0.01$, $c_1 = 1.5$, $c_2 = 1.7$, maxgen = 100, pop = 20. The process of searching parameter is given in Fig. 3. It can be seen from Fig. 3 that the optimal error is set to 0.05 and the overall training error decreases with algebra of evolution from 0.28 to 0.1, indicating the good stability of range.

3.4. Comparison with BP neural network

BP neural network is the core part of forward neural network as well as the essence of the artificial neural network. Using the same sample data, a 3 layer BP neural network based on PSO is established and the optimal weights and thresholds are determined by PSO algorithm. After repeated calculation, the basic structure of the network is 6-10-1. The data are normalized and ant-normalized by using mapminmax function. In particular, training period is 100, the learning rate is 0.1 and the training target is 10^{-5}.

In order to evaluate the performance and demonstrate accuracy of predictions between SVM and BP neural network, the statistical error analyses are chosen as follows:

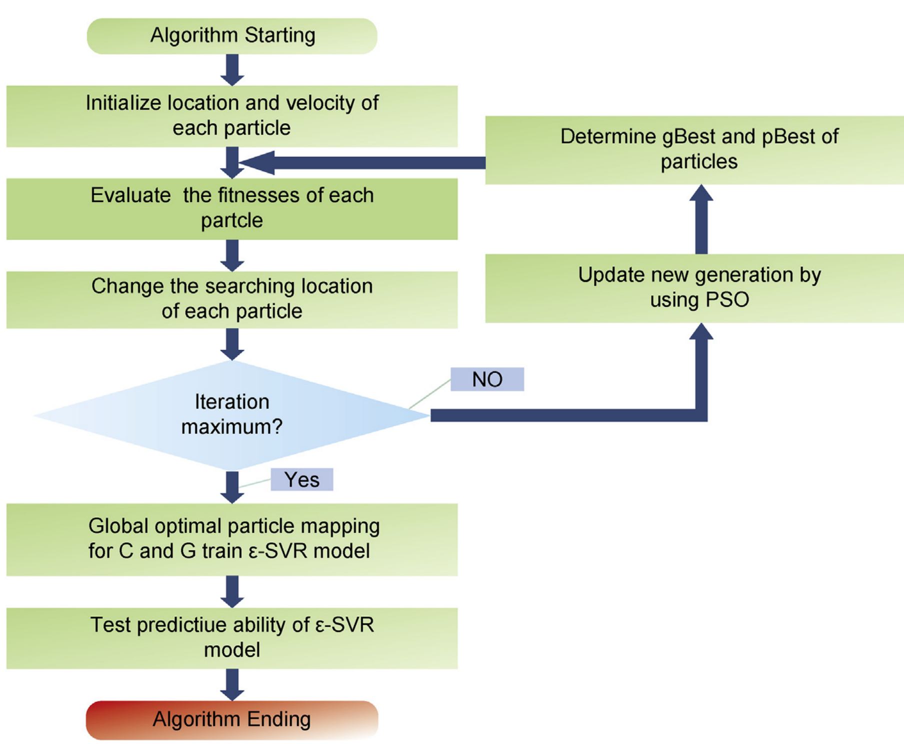

Fig. 2. Flowchart of parameter optimization for the PSO algorithm.

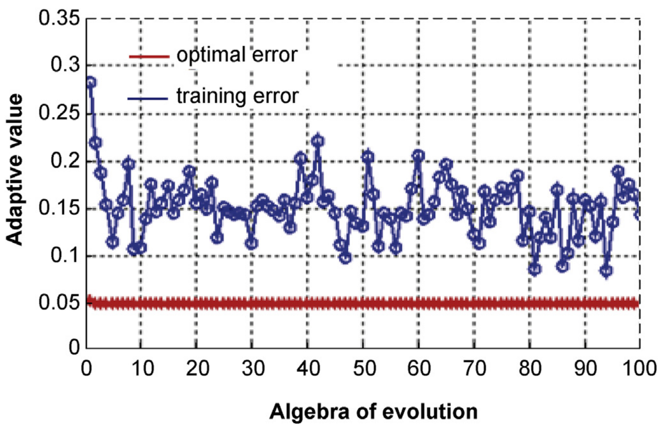

Fig. 3. Fitness curve in the process of optimization.

- *AARD* (average absolute relative deviation):

$$AARD = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_{cal} - y_{exp}}{y_{cal}}\right|_i \times 100\% \tag{10}$$

- R^2 (Correlation Coefficient): The correlation coefficient is a quantity that gives the quality of a least squares fitting to original data.

$$R^2 = 1 - \left[\frac{\sum\left|y_{cal} - y_{exp}\right|^2}{\sum y_{cal}^2}\right] \tag{11}$$

- E_{max} (Maximum absolute deviation): That is the maximum value among the difference between experimental value and forecast value.

$$E_{max} = Max\left|y_{cal} - y_{exp}\right| \tag{12}$$

- *RMS* (Root Mean Squared): this parameter is a criterion of data distribution around zero deviation line.

$$RMS = \left[\frac{\sum\left(y_{cal} - y_{exp}\right)^2}{N}\right]^{\frac{1}{2}} \tag{13}$$

where y_{cal} and y_{exp} are the calculated and experimental recovery factor, respectively.

The results of both PSO-BP and PSO-SVM models are listed in Table 2 and Fig. 4. The evaluation parameters of both models are shown in Table 3.

As can be seen from the Tables 2 and 3 and Fig. 4, the accuracy of PSO-SVM model ($AARD = 3.79\%$, $E_{max} = 2.75\%$, $RMS = 1.22\%$) is much better than that of the PSO-BP model ($AARD = 9.18\%$, $E_{max} = 5.44\%$, $RMS = 2.52\%$). The correlation coefficient ($R^2 = 0.997$) of the PSO-SVM model is much closer to 1. Moreover, the maximum absolute deviation and the root mean square error are less than those of the PSO-BP model. Nevertheless, the accuracy of empirical method from Oil and Gas Company is the worst among the methods considered in this work with $AARD = 10\%$ [9].

3.5. Outlier detection

Outlier detection (or diagnostics) is a novel testing technique for data reliability that can be of great significance in developing the mathematical correlations/models for the purpose of finding the applicability domain of a model [56–58]. The most fundamental process behind Outlier detection is to calculate leverage or hat indices and standardized residuals, then the H value is set as the abscissa and SR is regarded as the ordinate to map Williams diagram.

The specific calculation is as follows:

$$H = X\left(X^tX\right)^{-1}X^t \tag{14}$$

Where X is a two-dimensional ($n \times k$) matrix composing n data points (rows) and k parameters of the model (columns), and X^t denotes the transpose of matrix X. The diagonal elements of the H matrix are the hat values of the data in the feasible region of the problem. A warning Leverage (H^*) is normally fixed at $3(m+1)/n$, in which n is the number of data points and m is the number of model parameters.

$$\mathbf{SR} = \frac{y_i^{exp} - y_i^{\mathbf{pre}}}{\sqrt{\frac{1}{n-m-1}\sum_{i=1}^{n}\left(y_i^{exp} - y_i^{\mathbf{pre}}\right)^2(1 - H_{ii})}} \tag{15}$$

where SR is the standardized residuals (*SR*). The cut-off value (leverage = 3) is regarded to accept the data points within ±3 range standard deviations from the mean (to cover 99% normally distributed data). The existence of the majority of data points in the ranges of $0 \le H \le H^*$ and $-3 \le R \le 3$ reveals that both the data used for the model development and the data predicted by the developed model are in the applicability domain, demonstrating that the model is statistically valid.

According to the above calculation process, Outlier detections of PSO-SVM model and PSO-BP model can see Figs. 5 and 6. As shown in Figs. 5 and 6, the whole oil recovery factor data sets in the low-permeability reservoir can be declared to within the applicability domain of all models investigated in this work except one point in the corresponding data of PSO-BP

Table 2
Comparison of predicted recovery factors by different models.

K/mD	φ/%	μ/mPa s	H/m	ρ/well km^{-2}	γ	Unit/%				
						Exp.	PSO-BP	*AAD*	PSO-SVM	*AAD*
1.2	13.0	6.7	10.6	11.43	8.00	15.0	9.56	36.27	15.07	0.47
3.8	16.0	6.7	4.5	11.00	2.30	18.0	16.7	7.22	17.64	2.00
5.4	14.2	8.7	4.3	9.58	2.58	17.2	17.73	3.08	16.11	6.33
5.4	16.0	5.3	9.5	13.30	2.67	23.1	19.93	13.72	21.46	7.09
7.0	15.0	5.4	5.4	16.00	3.00	21.0	20.7	1.43	20.10	4.28
12.0	23.3	12.7	6.4	35.34	4.13	30.14	31.42	4.25	19.79	1.16
20.0	15.0	6.7	10.8	17.62	2.21	27.7	27.93	0.83	26.76	3.39
20.0	15.3	6.7	10.2	19.28	2.00	27.5	28.75	4.54	27.37	0.47
20.0	15.3	6.7	13.1	17.78	2.35	30.8	27.34	11.23	28.05	8.92

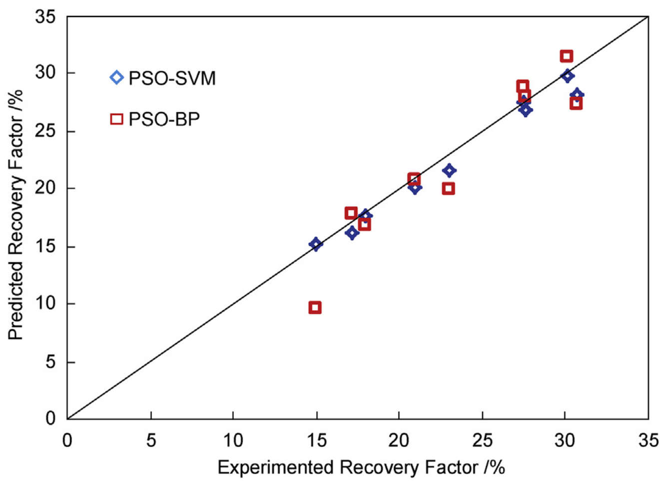

Fig. 4. A comparison of PSO-BP and PSO-SVM predictions with experimental recovery factors of the low-permeability reservoir.

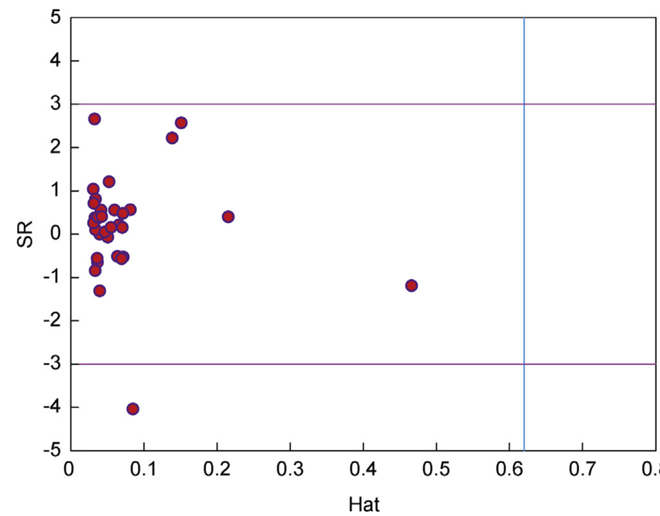

Fig. 6. Outlier detection and applicability domain for the PSO-BP model.

Table 3
Evaluation parameters of the BP and SVM models.

Parameter	BP model	SVM model
AARD/%	9.18	3.79
R^2	0.988	0.997
E_{max}/%	5.44	2.75
RMS/%	2.52	1.22

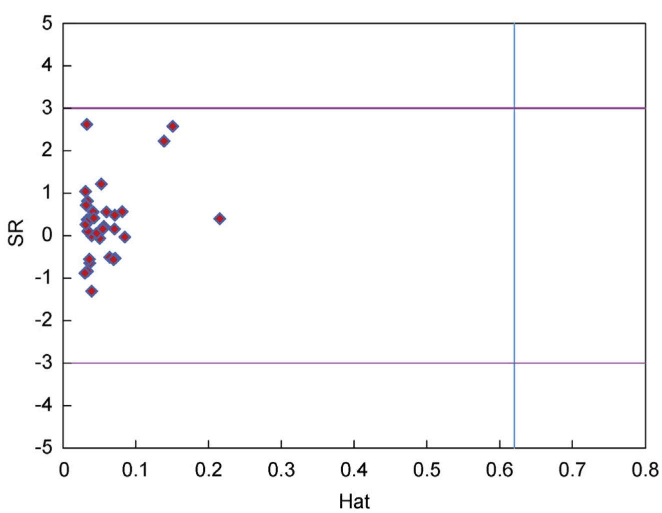

Fig. 5. Outlier detection and applicability domain for the PSO-SVM model.

located in the range of $R < -3$, which reveals that the PSO-SVM and PSO-BP investigated in this work are statistically correct and valid for representation/prediction of these experimental values.

4. Conclusions

In this work, a hybrid PSO-SVM-based model was proposed to predict oil recovery factor of the low-permeability reservoir. After a gray-correlation-analysis method was proposed to analyze the affecting factors of the recovery factor for low-permeability reservoir, the permeability, well spacing density, ratio of oil and water wells, porosity, effective thickness, and viscosity of crude oil were considered as input variables of the presented model, while oil recovery factor of low-permeability reservoir as output parameter. Moreover, a PSO-BP neural network model was also established to estimate the recovery factor. A comparison of the hybrid PSO-SVM-based model, PSO-BP neural network model and empirical method from Oil and Gas Company indicated that the proposed hybrid PSO-SVM-based model gives the best results for the investigated recovery factor of low-permeability reservoirs with $AARD = 3.79\%$ among all models considered in this work, and that the result of the PSO-BP neural network model is similar to that of empirical method from Oil and Gas company with *AARD*s of 9.18% and 10.0%, respectively. Furthermore, outlier diagnosis was performed on the whole data sets to identify the applicable range of all models investigated in this work by detecting the probable doubtful recovery factor data of the low-permeability reservoir with only one abnormal point.

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