Original Article

Development of ε-insensitive smooth support vector regression for predicting minimum miscibility pressure in CO$_2$ flooding

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Abstract

Successful design of a carbon dioxide (CO$_2$) flooding in enhanced oil recovery projects mostly depends on accurate determination of CO$_2$-crude oil minimum miscibility pressure (MMP). Due to the high expensive and time-consuming of experimental determination of MMP, developing a fast and robust method to predict MMP is necessary. In this study, a new method based on ε-insensitive smooth support vector regression (ε-SSVR) is introduced to predict MMP for both pure and impure CO$_2$ gas injection cases. The proposed ε-SSVR is developed using dataset of reservoir temperature, crude oil composition and composition of injected CO$_2$. To serve better understanding of the proposed, feed-forward neural network and radial basis function network applied to denoted dataset. The results show that the suggested ε-SSVR has acceptable reliability and robustness in comparison with two other models. Thus, the proposed method can be considered as an alternative way to monitor the MMP in miscible flooding process.

Keywords: CO$_2$ flooding, minimum miscibility pressure, ε-insensitive smooth support vector regression, feed-forward neural network, radial basis function network

1. Introduction

Miscible flooding is considered to be an effective enhanced oil-recovery (EOR) method which is gaining increasing popularity for applications in the upstream oil industry. The most common fluid used for miscible displacement is carbon dioxide (CO$_2$) because of its lower cost, high displacement efficiency, and the potential for concomitant environmental benefits through its disposal in the petroleum reservoir (Mungan, 1991; Wassmuth*et al.,* 2005; Yuan *et al.,* 2004). The most important parameter required for evaluating and designing a miscible flood is the minimum miscibility pressure (MMP), in which local displacement efficiency from CO$_2$ is a function of the MMP. At this pressure, the injected gas can develop miscibility dynamically through a multi-contact process with the crude oil at reservoir temperature. If the displacement process is represented as a one-dimensional dispersion-free flow (piston-like flow), at the MMP, the displacement efficiency approaches 100% (Jaubert *et al.,* 2001; Nasrifar & Moshfeghian, 2004).

This paper presents a novel and robust model namely ε-insensitive smooth support vector regression (ε-SSVR) to estimate impure and pure CO$_2$–oil MMP. All of the oil and gas properties and reservoir conditions are considered to develop the model. The performance of the proposed model is compared to those of other predictive model by means of some statistical indices. To the best of our knowledge, a predictive model based on ε-SSVR for prediction of CO$_2$-oil MMP has not presented in the literature before.

The rest of the paper is organized as follows. Next Section describes the problem. Proposed ε-SSVR method is explained in Section 3. Simulation results are provided in Section 4 to demonstrate the effectiveness and potential of the proposed ε-SSVR for CO$_2$-oil MMP prediction compared with feed-forward neural network using the same observed data. Finally, some conclusions are included in Section 5.

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2. Problem Definition

Accurate determination of MMP is one of the crucial tasks to design and manage an efficient gas injection EOR projects. Several experimental and theoretical methods have been proposed in the literature. The primarily available experimental procedures to measure MMP under reservoir conditions are the slim tube displacement, rising-bubble apparatus (RBA) and vanishing interfacial tension (VIT). Slim tube displacement is regarded as the "petroleum industry standard" to determine the MMP in which the miscibility conditions are determined indirectly from oil recovery (Ahmadi & Johns, 2008). This technique is strongly dependent on the packed grain sizes because of difference in the pore throat sizes and related pore invasion pressure owing to capillarity. In the rising bubble apparatus, the MMP is determined from the observations of changes in size, shape, or color of the injected gas bubble in its rising process through a thin transparent column of crude oil. The vanishing interfacial tension technique is based on the interfacial tension measurement between the reservoir crude oil and injected gas at reservoir temperature and at varying pressures or enrichment levels of gas phase. The pressure at which interfacial tension approaches zero is defined as MMP.

Unfortunately, there is no a standard design, no standard operating procedure, no standard set of criteria for determining miscibility in slim tube (Elsharkawy et al., 1996). Moreover, to avoid undesirable effects of fingering, transition zone length and transverse compositional variations, it is generally necessary to perform several slim tube displacement tests with extremely low flow rates, long lengths and smaller diameter tubing. Therefore this technique is generally time-consuming and requires high computational efforts (Ayirala & Rao, 2006). The RBA technique simulates only the vaporizing process in the miscibility development process and disregards the condensing process (Gu et al., 2013). Moreover, it has some drawbacks including subjective interpretation of miscibility, lack of any quantitative information and some arbitrariness related to miscibility evaluation (Ayirala & Rao, 2007). Orr Jr. and Jessen (2007) showed that MMP measurement obtained by VIT depends strongly on the composition of the gas–oil mixture used.

Hence, development of an accurate approach for determination of the natural gas–oil MMP is necessary. A number of correlations have been reported as substitutes for conventional experimental methods (Emera & Sarma, 2005; Glass, 1985; Holm & Josendal, 1974; Klins, 1984; Lange, 1998; Shokir, 2007; Wang & Orr, 2000; Yellig & Metcalfe, 1980). However, the applicability of the correlation techniques is extremely limited to a specific oil reservoir. Correlation technique proposed by Chen et al., (2013) has the limitation of temperature, pressure and molecular weight of the C_{7+}. Zarenezhad (2016) proposed a correlation method according to the modification of original Firoozabadi and Aziz (1986). This method has the limitation of determination of the optimum values of the parameters in which determine according to the experimental data. For this reason, an investigation for a more adaptable and reliable calculation of MMP is necessary. In the recent years, computational intelligence systems have proven to be alternative way for system analysis and prediction because of their powerful ability to reflect the system's complexity and the high degree of confidence and precision. Huang et al., (2003) developed a neural network (NN) model to predict MMPs for both pure and impure CO_2 MMP of oils. Dehghani et al., (2008) proposed a hybrid neural genetic algorithm to predict CO_2 MMP by considering the reservoir temperature, reservoir fluid composition, and injected gas composition as input parameters and the CO_2 MMP as desired parameter. Tatar et al., (2013) developed an intelligent model for CO_2-reservoir oil MMP using radial basis function NN algorithm over a broad range of reservoir temperature, oil and drive gas compositions.

The literature demonstrates that some articles have been published in the favor of using various type of artificial neural networks in CO_2 MMP modeling and forecasting as a function of reservoir temperature and the compositions of oil and injected gas (Chen et al., 2013; Alomair and Garrouch, 2015; Hemmati-Sarapardeh et al., 2016; Mollaiy-Berneti, 2016). An adaptive neuro-fuzzy inference system (ANFIS)–based correlation has been developed by Kivi et al., (2013) to estimate the MMP values. Although these methods are useful, there are some inherent drawbacks often encountered in the use of the back propagation (BP) algorithm with gradient-descent approach as a commonly used training algorithm of these methods. Firstly, the BP algorithms are prone to become trapped in local optimum particularly for complex function approximation problems. Second, the convergence speed of the BP algorithm is very slow.

3. ε-Insensitive Smooth Support Vector Regression

Support Vector Machine (SVM) with linear or nonlinear kernels is one of the most supervised learning algorithms for pattern classification as well as regression (Smola & Schölkopf, 2004; Vapnik, 1995). SVM maps the data from the original space into a higher-dimensional space through the kernel function and then estimates the optimal separating hyperplane under the constraint of a maximal margin. The typical nonlinear separating function will be obtained by retransforming the separating hyperplane into the original space of variables (Vapnik, 1995). For regression problems, Vapnik introduced a ε-insensitive loss function to original SVM which sets an ε-insensitive tube around the data. This method is referred to as ε-insensitive support vector regression (ε-SVR) (Smola & Schölkopf, 2004).

As an improved version of ε-SVR, a smoothing strategy for solving ε-SVR, named ε-insensitive smooth support vector regression (ε-SSVR), was proposed in (Lee et al., 2005). By using ε-SSVR formulation, it only need to solve a set of linear equations iteratively instead of solving a convex quadratic programming problem, as is the case with a conventional ε-SVR (Lee et al., 2005). The procedure of the ε-SSVR is described as follows. Given a regression problem, consider the training dataset to be $S = \{(x_1, y_1),...,(x_m, y_m)\}$, where m is the number of observation. In regression problem, the objective is to find a function f(x) that tolerates a small error in fitting the training dataset. Based on the concept of SVM, f(x) is made as flat as possible in fitting the training dataset. We start with the linear form of f(x) which is expressed as f(x)=x^Tw+b. The problem can be expressed as the following unconstrained minimization problem:

$$\min_{(w,b)\in \mathbb{R}^{n+1}} \frac{1}{2} w^T w + C 1^T \left| \xi \right|_\varepsilon \tag{1}$$

where $\left(\left| \xi \right|_\varepsilon \right)_i = \max\{ \left| A_i w + b - y_i \right| - \varepsilon \}, i = 1, ..., m,$

is the ε-insensitive loss and C>0 is the regularization parameter that weights the tradeoff between the flatness of f(x) and the amount up to which deviations larger than ε are tolerated. To deal with the ε-insensitive loss function, conventionally, above minimization problem is reformulated as a convex quadratic minimization problem (Smola & Schölkopf, 2004).

Lee *et al.*, (2005) modified the problem slightly and solved it directly as an unconstrained minimization problem. They used the square of 2-norm of the ε-insensitive loss with weight C/2 instead of the 1-norm of the ε-insensitive loss as in Equation 1 and added the term $b^2/2$ in the objective function leading to strong complexity unique global optimal solution. These modifications yield the following unconstrained minimization problem:

$$\min_{(w,b)\in \mathbb{R}^{n+1}} \frac{1}{2}(w^T w + b^2) + \frac{C}{2}\sum_{i=1}^{m} \left| A_i w + b - y_i \right|_\varepsilon^2 \tag{2}$$

For all $x \in \mathbb{R}$ and $\varepsilon > 0$, we have $\left| x \right|_\varepsilon^2 = (x-\varepsilon)_+^2 + (-x-\varepsilon)_+^2$, where x_+ is a plus function. In practice, the following smooth p-function is usually used to approximate x_+:

$$p(x, \alpha) = x + \frac{1}{\alpha} \log(1 + \exp(-\alpha x)) \tag{3}$$

where $\alpha > 0$ is the smoothing parameter. Therefore, $\left| x \right|_\varepsilon^2$ can be replaced by a very accurate smooth approximation given by:

$$p_\varepsilon^2(x, \alpha) = (p(x-\varepsilon, \alpha))^2 + (p(-x-\varepsilon, \alpha))^2 \tag{4}$$

By replacing the square of the ε-insensitive loss by p_ε^2-function, the smooth reformulation of Equation 2 is given by:

$$\min_{(w,b)\in \mathbb{R}^{n+1}} \frac{1}{2}(w^T w + b^2) + C 1^T p_\varepsilon^2(Aw + 1b - y, \alpha) \tag{5}$$

where $p_\varepsilon^2(Aw+1b-y, \alpha)_i = p_\varepsilon^2(A_i w + 1b - y_i, \alpha), i = 1, ..., m \cdot$ Since the objective function in this problem is strongly convex and infinitely differentiable, problem has a unique solution that can be solved efficiently using a fast Newton–Armijo method. The solution of Equation 2 can be attained by solving Equation 5 with α approaching infinity (Lee *et al.*, 2005).

For the function with nonlinear form, the duality theorem in convex minimization problem (Mangasarian, 2000; Musicant & Feinberg, 2004) and the kernel technique (Vapnik, 1995) are applied. The observation $y \in \mathbb{R}^m$ is approximated by $y \approx K(A, A^T)u + 1b$, where $K(A, A^T)$ is a nonlinear kernel with $K(A, A^T)_{ij} = K(A_i, A_j^T)$. Using the same loss criterion with the linear case, the regression parameter $u \in \mathbb{R}^m$ and the bias $b \in \mathbb{R}$ are determined as follows:

$$\min_{(u,b)\in \mathbb{R}^{m+1}} \frac{1}{2}(u^T u + b^2) + \frac{C}{2}\sum_{i=1}^{m} \left| K(A_i, A^T)u + b - y_i \right|_\varepsilon^2 \tag{6}$$

The nonlinear form of ε-SSVR is obtained by repeating the same arguments in going from Equation 2 to Equation 5 as follows:

$$\min_{(u,b)\in \mathbb{R}^{m+1}} \frac{1}{2}(u^T u + b^2) + \frac{C}{2} 1^T p_\varepsilon^2(K(A, A^T)u + 1b - y, \alpha) \tag{7}$$

where $p_\varepsilon^2(K(A, A^T)u + 1b - y, \alpha)_i = p_\varepsilon^2(K(A_i, A^T)u + 1b - y_i, \alpha), i = 1, ..., m \cdot$ It should be mentioned that this problem still retains the strong convexity and differentiability properties for any arbitrary kernel. By applying the Newton-Armijo Algorithm method, the solution of Equation 7 leads to the nonlinear regression function as follows:

$$f(x) = \sum_{i=1}^{m} u_i K(A_i, x) + b \tag{8}$$

4. Results and Discussion

4.1 Data treatment

In this study reservoir temperature, molecular weight of the C_{5+} fraction in crude oil, composition of injected gas (C_1, N_2, C_2-C_4, H_2S and CO_2) and the ratio of volatile (C_1 and N_2) to intermediate (C_2-C_4, H_2S and CO_2) components in crude oil were taken as the input parameters and correspond CO_2-oil MMP was dedicated to be output. These inputs are selected owing to their dependency with CO_2-oil MMP which has been proved in several studies (Emera & Sarma, 2005; Nasrifar & Moshfeghian, 2004; Shokir, 2007; Wang & Orr, 2000; Yuan *et al.*, 2004). Data sets were gathered from the published literatures. Details of these parameters are given in Table 1.

Table 1.   Range of input/output data used in model development.

Parameter	Minimum	Maximum	Unit
Temperature (K)	32.20	118.30	^oC
CO_2	40	100	%
H_2S	0.00	75	%
N_2	0.00	8.08	%
C_1	0.00	20	%
C_2-C_4	0.00	20	%
MW C_{5+}	171.1	240.70	g/mol
Volatile/intermediate	0.00	9.16	_-_
MMP	6.53	28.17	MPa

Before starting modeling process, to avoid saturation problem and consequently low rate training, normalization of data is necessary. In this study, all source data were normalized to the range [0.1, 0.9] by the following equation:

$$x_{Normalized} = 0.8 \times \left(\frac{x_i - x_{min}}{x_{max} - x_{min}} \right) + 0.1 \tag{9}$$

where x_i is the variable of the database, x_{max} and x_{min} are the maximum and minimum values in the database, respectively. In order to avoid overfitting, 70% of collected dataset selected for training the model and remaining 30% considered for testing to validate the accuracy of the model.

Train and test sets must be different and were selected randomly from the original data set.

4.2 Evaluation methods

Three statistical parameters that can reflect the relationships between the predicted values and the experimental values were used as evaluation indexes, i.e. mean absolute error (MAE), root mean square error (RMSE) and coefficient of determination (R^2). These statistical parameters show an average behavior of error in the model performance and are overall statistics that do not show the error distribution over results. The mathematical expressions for these measures are given as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_i^{pre} - y_i^{exp}\right| \tag{10}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i^{pre} - y_i^{exp})^2} \tag{11}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i^{exp} - y_i^{pre})^2}{\sum_{i=1}^{N}(y_i^{exp} - \overline{y}^{exp})^2} \tag{12}$$

where N is the number of the training or validation samples, y_i^{exp}, y_i^{pre} and $\overline{y}^{exp}$ are the experimental, predicted, and average of experimental values, respectively. The higher value of R^2 and a lower value of MAE and RMSE mean a better performance of the model.

4.3 Simulations and results

Proposed ε-SSVR was designed for different values of C, g and ε, and the ones that attained relatively good performance were selected. The weight parameter C in support vector learning took values from {10, 100, 1000, 10000}; g is a gamma parameter in kernel function which took values in the range [0.1, 0.7] with step one-tenth; and the insensitivity value ε took values from {0.01, 0.05, 0.1}. All the experiments were run on a personal computer with Intel(R) Core(TM)2 Duo CPU (2.20 GHz) processor, 3.00 GB memory, and Windows 7.0 operation system. The results for proposed ε-SSVR trained with different values of C, g and ε are shown in Figures 1-3. It can be deduced that the best performance is accompanied by C=10,000, g=0.7 and ε=0.01.
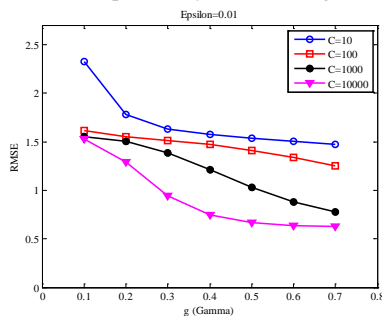

Figure 1.   Sensitivity of root mean square error (RMSE) produced by ε-SSVR for ε=0.01 versus different values of C, g in CO₂-oil MMP prediction.
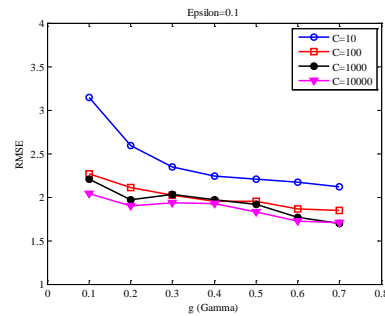

Figure 2.   Sensitivity of root mean square error (RMSE) produced by ε-SSVR for ε=0.01 versus different values of C, g in CO₂-oil MMP prediction.
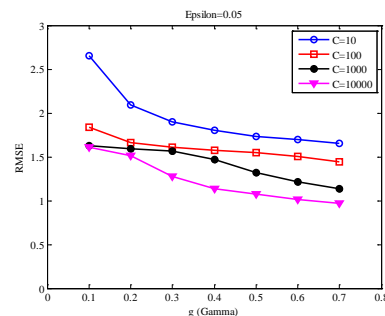

Figure 3.   Sensitivity of root mean square error (RMSE) produced by ε-SSVR for ε=0.01 versus different values of C, g in CO₂-oil MMP prediction.

The comparison between experimental CO_2-oil MMP and proposed ε-SSVR method predicted values is shown in Figure 4 for training and testing phases. As shown in this figure, the relationship between input parameters (reservoir temperature and the compositions of oil and injected gas) and CO_2-oil MMP is nonlinear. Also the proposed model and other FFNN and RBF methods model the relationship between input-output data based on an average behavior of error in the model performance and do not consider the error distribution over results. For this reason, some errors between experimental and predicted data are very small and other's errors are relative large. Figure 5 shows a scatter plot of experimental values against predicted values. It can be seen that the proposed ε-SSVR predicts closely follow the experimental values.
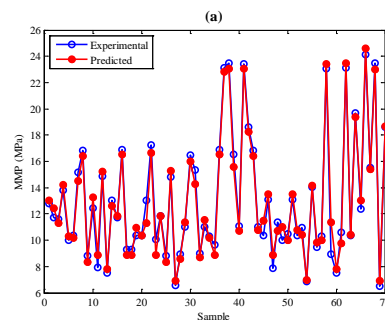

Figure 4.   Comparison between experimental values of CO₂-oil MMP and ε-SSVR predicted values (a) train phase, (b) test phase.
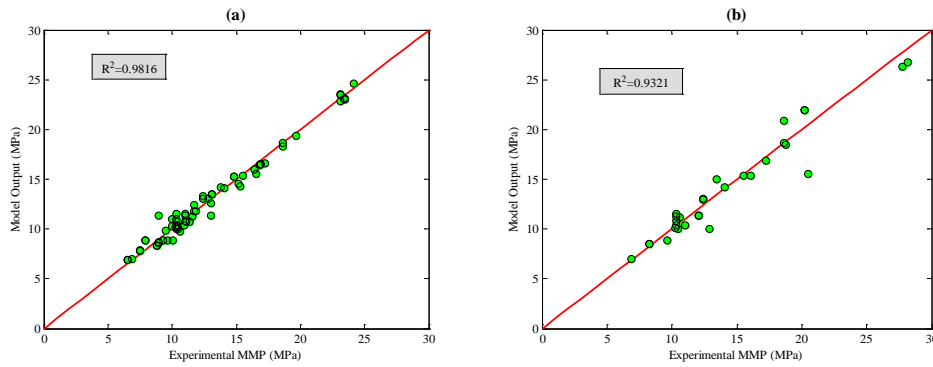
Figure 5.   Scatter plot of obtained results by proposed model in comparison with experimental values (a) train phase, (b) test phase.
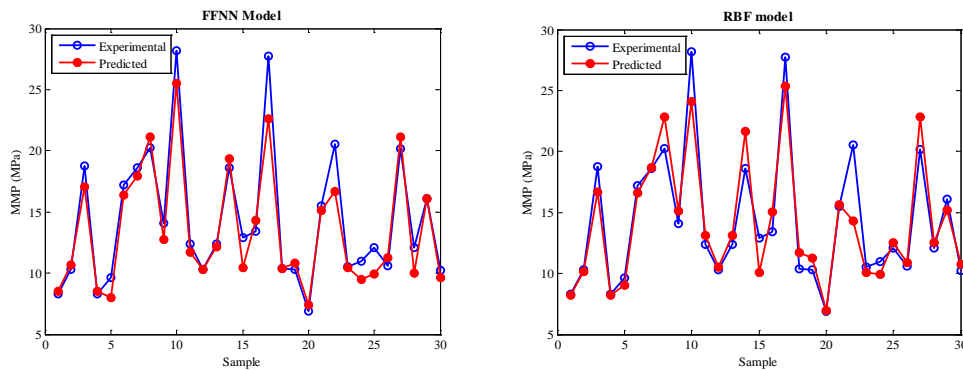

Figure 6.   Comparison between experimental values of CO_2-oil MMP and predicted values of FFNN and RBF network.
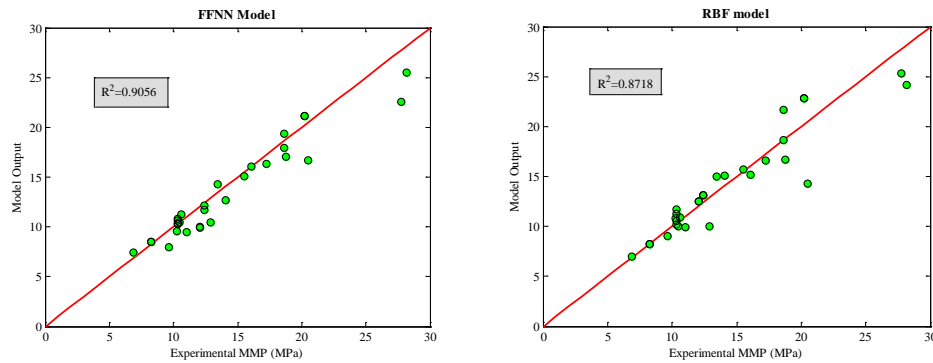

Figure 7.   Scatter plot of obtained results by FFNN and RBF models in comparison with experimental values.

To have a true evaluation of the potential of proposed ε-SSVR method, feed-forward neural network (FFNN) (Huang *et al.,* 2003) and radial basis function (RBF) network (Tatar *et al.,,* 2013) as two methods applied in the literature were also constructed using the same input parameters.

A three-layer FFNN was designed using Levenberg–Marquardt training algorithm. Different ANN architectures and transfer functions were tried by a trial-and-error. It was found the 8-10-1 (8 input neurons, 10 hidden neurons and 1 output neuron) architecture was the optimum model in terms of mean squared error whereas log-sigmoid and linear transfer functions in hidden and output neurons, respectively, gave the best results. The value of learning rate 0.01 and momentum constant 0.9 were used for the Levenberg–Marquardt algorithm (default in MATLAB

software). A training performance goal (mean square error) was set to 0.0. Using MATLAB and its powerful neural network toolbox, the RBF model was developed with maximum number of 20 neurons.

In Figure 6 experimental values of CO_2-oil MMP and the CO_2-oil MMP predicted by FFNN and RBF models were plotted in testing phase. As it is seen, due to the limitation of low velocity of convergence and easily getting into local minimum of BP training algorithm, these methods has lower performance in comparison with ε-SSVR. Figure 7 shows a scatter plot of experimental values against predicted values of those models for testing set. For more statistical analysis, the error distribution of different approaches for testing phase is depicted in Figure 8. As seen, proposed method has a lowest mean and standard deviation error compared to two other methods. Table 2 provides a
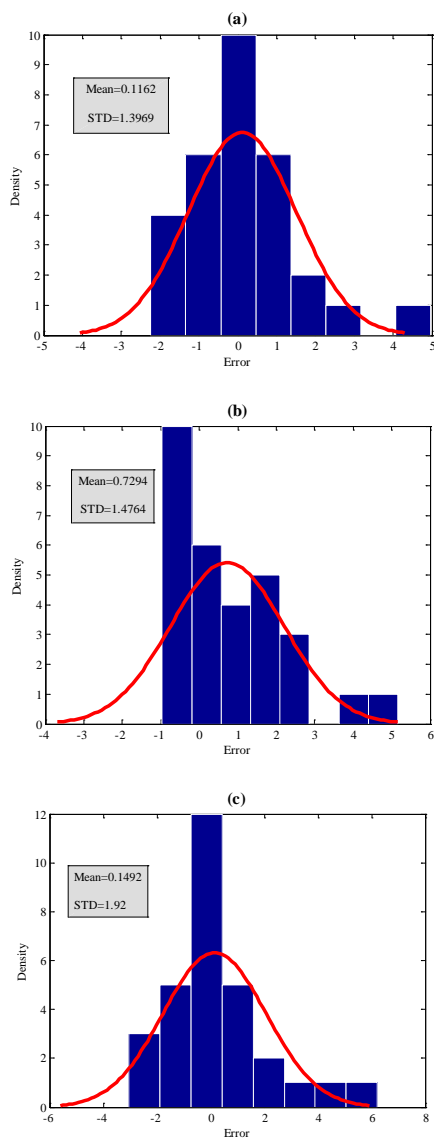
Figure 8.   Error distribution of (a) ε-SSVR (b) FFNN model (c) RBF model.

Table 2.   Statistical results of proposed model, FFNN and RBF models.

Model	MAE	RMSE	R^2
FFNN model [20]	1.1338	1.6245	0.9056
RBF model [22]	1.2792	1.8936	0.8718
proposed model	0.9326	1.3783	0.9321

comparison analysis of the performance obtained by the proposed ε-SSVR with the respective performances of FFNN and RBF methods. These results imply that the prediction performance of the proposed ε-SSVR is better than the two other models, where most points have the best agreement with experimental data and, both values of MAE and RMSE are smaller and coefficient of determination is also closer to unity.

5. Conclusions

Considering the importance of MMP in the screening of potential reservoirs for miscible gas injection projects, and high expensive and time-consuming of experimental determination of MMP, an attempt was made in this study to investigate the application of ε-insensitive smooth support vector regression for prediction of CO_2–oil MMP. The following conclusions are drawn based on the simulation results:

1. The proposed ε-SSVR is capable of predicting CO_2–oil MMP with dataset of reservoir temperature, molecular weight of the C_{5+} fraction in crude oil, composition of injected gas (C_1, N_2, C_2-C_4, H_2S and CO_2) and the ratio of volatile (C_1 and N_2) to intermediate (C_2-C_4, H_2S and CO_2) components in crude oil.
2. The prediction performance efficiency of the proposed method has been verified by comparing with feed-forward neural network and radial basis function network which employed in the literature.
3. Since dataset used in this study included pure and impure CO_2 streams, the proposed method is valid for both pure and impure CO_2 injection cases.
4. The proposed ε-SSVR can be considered as an alternative method of experimental techniques due to its inexpensiveness, time-saving, high adaptability and accuracy.

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