CMTC-486642-MS

Applicability of Worldwide CO_2 Worldwide Immiscible Flooding and Prediction

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This paper was prepared for presentation at the Carbon Management Technology Conference held in Houston, Texas, USA, 17-20 July 2017.

Abstract

Carbon dioxide (CO_2) flooding is a mature technology in oil industry that finds broad attention in oil production during tertiary oil recovery (EOR). After about five decades of developments, there have been many successful reports for CO_2 miscible flooding. However, operators recognized after considering the safety and economics that achieving miscible phases is one of big challenge in fields with extremely high minimum miscible pressure (MMP). Compared with CO_2 miscible flooding, immisible flooding of CO_2 demonstrates the great potential under varying reservoir/fluid conditions. A comprehensive and high-quality data set for CO_2 immiscible flooding is built in this study. Valuable guildelines have been concluded,and production prediction models are established to further assist the applicability of new projects for the first time. Results show that along with the current method in literature to find applicability guidelines, prediction models involved with important operation and prodcution parameters help to increase the accuracy of CO_2 immiscible applicabilities. Data involved in this study are checked for independence for feature selection before utilization. We also find that support vector machine could predict the enhanced oil production rate and CO_2 injection efficiency better than multiple linear regression method based on the data set. Furthermore, the multiple linear regression method build an excellent model for the prediction of enhanced oil recovery with an accuracy of almost 100%.

Introduction

A prodiction model is a tool for decision making and problem solving that has been applied in variety of fields (e.g., medical science [1-3], meteorology [4], transportation [5, 6], business [7, 8], biology [9, 10], and chemistry [11, 12]) for further applicability evaluation. Eagle et al. built a prediction model to accurately estimate the risk of six month mortality after patients have been hospitalized for acute coronary syndrome (ACS), which provides guidance of the intensity of therapy to clinicians in clinical medicine [13]. Gendt et al. established a numerical weather prediction model to help people to make plans for many activities (e.g., farmers to find the best time for harvest; pilots to schedule the safest path, etc. [14]). In a prediction model, prediction accuracy mainly depends on the methodology of prediction and the quality of data that fed into the model, which is one of the crucial indicator to evaluate the effectiveness of models that researchers spare no efforts to pursue as high of an accuracy as possible.

Based on literature, prediction methodology has changed dramatically. In the past, most of prediction models were established based on equations and experience [15]. With the worldwide development of advanced technology in recent years, implementing machine learning to build prediction models is becoming a topic of interest. This method feeds the model not only with expert experiences, but also with algorithms to reveal the unknown information, which increases prediction accuracy. On the other hand, data quality problems which involves consistency, redundancy, missing data, wrong data, and feature selection, affect the prediction accurancy as well. Although enhancing the data quality may increase the prediction accuracy even more [16, 17], fewer attentions have been put onto the data quality improvement. If poor data are fed into the model, then the predicton model will be misleading. In oil industry, prediction models have been applied for drilling [18], production [19, 20], reservoir characterization [21], and well completion [22]. As one of the important enhanced oil recovery (EOR) techniques, prediction models for CO_2 immiscible flooding have been found to select EOR methods [23]. The primary mechenisms of CO_2 immiscible flooding that contribute to improving oil recovery are oil viscosity reduction, oil swelling, interfacial tension reduction, and blowdown. During the injection of CO_2 into reservoirs, CO_2 dissolves into oil, which significantly reduces oil viscosity. Furthermore, lab experiments have demonstrated that the higher the oil viscosity, the higher the viscosity reduction [24]. Also, oil volume increases about 10-35% based on various reservoir situations due to the dissolution of CO_2 [24, 25]. Based on current research studies, the main reasons for implementing CO_2 immiscible flooding worldwide are the immisciblity and situations on site. Minimum miscible pressure (MMP) is defined as the lowest pressure where oil and injectants achieve miscibility dynamically [26], and CO_2 displacement with reservoir pressures less than MMP are considered as CO_2 immiscible flooding. Extremely high temperatures could lead to immiscibility because MMP is positively correlated with temperature [15], which means that the higher the reservoir temperature, the higher the MMP, and the harder the development for miscibility. Current situations were considered before applying CO_2 immiscible displacement. For example, Halfmoon field (Wyoming, 1992) had poor response for water flooding, but had CO_2 sources on site [27], whereas Buracica field (Bahia, 1991) had conducted CO_2 injection for 15 years for EOR activities and had CO_2 vented [28].

Although some positive results have been reported in prediction models of CO_2 flooding [29] and some screening criteria have been established [30], prediction models of CO_2 immiscible flooding that help to determine the applicability and guidelines have been merely studied. Moreover, the accuracy of existing applicability studies could be improved since most of the studies yielded at the stage of reservoir parameter analysis without considering other valuable production parameters for further economic evaluation (e.g., increased oil recovery, CO_2 injection efficiency). Most prediction models and applicability guidelines only consider the flooding applicability, but barely mention the economic applicability or the data quality problems. In fact, CO_2 immiscible project data in oil field are scattered and are in a variety of formats. Even though Oil and Gas Journal Biannually EOR Surveys where reservoir and fluid information have been collected for CO2 immiscible flooding have conducted significant efforts, partial important operation parameters and production parameters are still missing (e.g., CO_2 utilization efficiency, CO_2 injection rate, well spacing, etc.). Moreover, severe data quality problems have been found, which leads to bias or misleading results [31].

In order to make prediction results more applicable for CO_2 immiscible flooding, we try to collect and organize a high-quality CO_2 immiscible data set that will lay the foundation for further analysis, reasoning, and decision making. This data set helps operators to better select and determine the most suitable CO_2 immiscible flooding methods. Instead of only using reservoir parameters, some non-negligible evaluation parameters are added into our applicability guidelines for better economic consideration.

Data Collection and Preparation

The data set was created by collecting information from variety of data sources including books, DOE reports, AAPG database, *Oil and Gas Biannually EOR surveys*, fields, and SPE publications. All data were extracted from original data sources, and saved into the same data collection system. The first CO_2 immiscible flooding project was found in Ritchie Field (Arkansas, USA) which took place in 1968 [32]. Motivated by the success of this field, the second CO_2 immiscible project in United States was conducted in the nearby Lick Creek Field in 1975, where 7.6 Bscf of CO_2 was injected into a reservoir with a net thickness of 8.6 ft and an oil gravity of 17 °API. Over the decades, a considerable number of CO_2 immiscible projects have been undertaken in United States and in China, Turkey, Trinidad, Malaysia, Hungary, Argentina, Canada, and Brazil. Aftering collecting all the raw data, inconsistent and redundant data have been checked and deleted to keep the data high quality. As a result, 41 projects from 35 different oil fields were collected.

Figure 1 and Figure 2 summarise the number of projects and distributions of the projects that have been collected. In Figure 1, the gap between the cumulative number of projects and the number of projects in each year represents the total number of projects that has ceased until that specific year. From the figure, CO_2 immiscible projects increased dramatically in the early 1980s because gas injection techniques were considered as a proming, but not well understood EOR method in which different gas injectants were applied in various fields. More CO_2 immiscible projects and other gas injection projects came out at the same time. Several projects were ceased in 1985 and 1986 due to the low oil price. After that, the number of projects gradually increased. Figure 2 indicates that United States is the leader for using CO_2 immiscible technique and occupies 46% of all projects. The pie chart shows the distribution of projects in the United States, where most of projects were conducted in states with valuable CO_2 sources due to the construbtion of CO_2 pipelines.

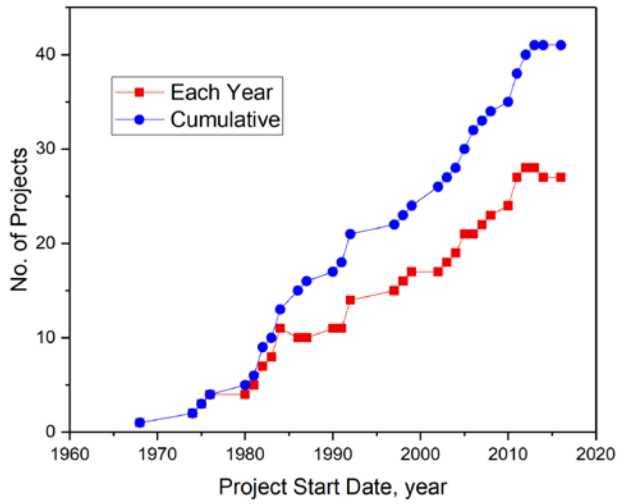

Figure 1. Number of CO_2 immiscible applications since 1968

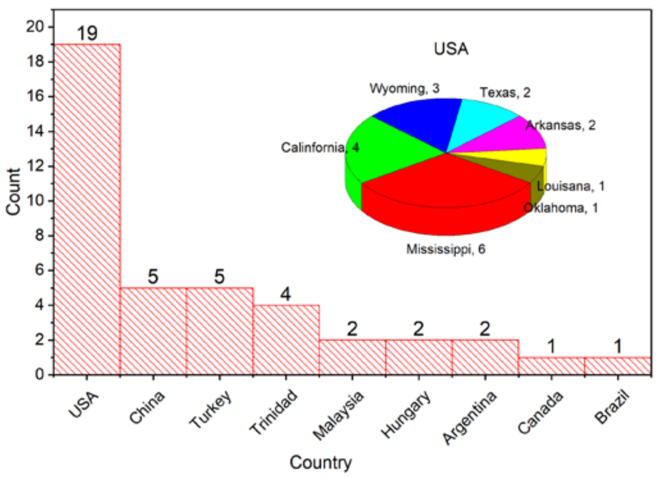

Figure 2. CO_2 immiscible application distribution

Screening Criteria Update

Fundamental statistics have been utilized to study the suitable ranges for CO_2 immiscible projects. Boxplots are used to show the minimum, Q1 (25 percentile), median, Q3 (75 percentile), maximum, and to detect special cases [31]. Figure 3 depicts the ranges of important reservoir / fluid properties and the enhanced oil recovery. From the figure, it is surprise to find that CO_2 immiscible displacement has been successful applied in shallow reservoirs up to 1400 ft (Yates, USA), and also in deep reservoirs up to 8500 ft (Martinville, USA). The reservoir pressure is lower in shallow reservoirs due to the overburden pressure. In deep reservoirs, even though the reservoir pressure is higher, the temperature is high as well, and since MMP is highly related to oil composition and temperature [15], the MMP is hard to achieve. Therefore, miscibility is difficult to obtain for both shallow and deep reservoirs with the injection of CO_2. The MMP values are greater than 1000 psi and less than 4322 psi, but most projects fall into the range of 1470 to 2440 psi. Permeability has a wide range, and 75% of projects are less than 465 mD. From the boxplots of viscosity and oil gravity, most CO_2 immiscible projects are conducted into the heavy oil reservoir (10-25 °API), especially in Turkey. The main net thickness for implementing CO_2 immsicble technique ranges from 18 to 141 ft. The thinnest reservoir is found in China (Yaoyingtai field), and the thickest reservoir is located in the United States (Huntington Beach field). Most reservoir temperatures are from 120 to 152 °F, but the temperature is extremely high in China and Hungary because the location of formation is very high [22, 33, 34].

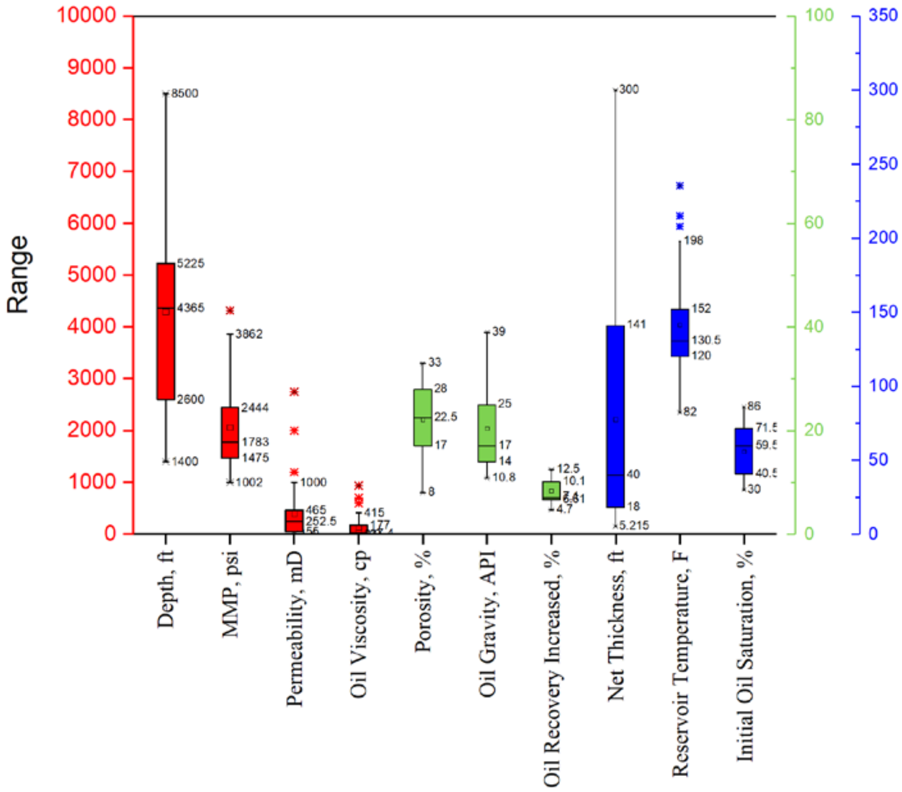

Figure 3. Boxplot of depth, MMP, permeability, oil viscosity, porosity, oil gravity, enhanced oil recovery, net thickness, reservoir temperature, and initial oil saturation. The colors of boxplots are mathed with the color of vertical axis where values for red, green, blue boxplots are read from red, green, and blue axis, respectively.

Even though the projects beyond the wiskers are declared as outliers [35], these projects should be considered as special cases in oil industry because they are not biased and were successfully implemented in the field. From the figure above, special cases were found based on boxplots of MMP, permeability, viscosity, and reservoir temperature. Tables 1 and 2 summarise the field names with minimum or maximum oberservations and the detailed information for all special cases, respectively.

Table 1. Minimum and maximum field names for each reservoir/fluid parameters.

Properties	Fields	
	min	max
Porosity	Chihuido de la Sierra Negra	Paradis, Lick Creek
Permeability	Changqing	Ritchie
Depth	Yates	Martinville
Net Thickness	Yaoyingtai	Huntington Beach
Reservoir Temperature	Yates	Szank
Initial Oil Saturation	Martinville	Tinsley, West Hastings
MMP	Yates	Tuha
Oil Gravity	Camurlu	Salt Creek
Oil Viscosity	Dulang	Ikiztepe

As shown in Table 1, Yates field has the minimum values for depth, reservoir temperature, and MMP. The reason for this could be the target formation is a shallow reservoir, which makes the reservoir temperature very low, and the MMP value is lower.

Table 2 depicts that all special cases detected from permeability happened in the United States, while special cases illustrated in the MMP boxplot were found in China. Projects in Turkey and Hungary have the special cases for oil viscosity and reservoir temperature, respectively. It is not a coincidence that all special cases for each reservoir parameter are from the same country because the reservoir characteristics in each country are uniqe. For example, all projects in China are located at deep reservoirs with a minimum depth of 5495.5 ft. Projects in China normally have high asphaltene content (high molecular weight). This special condition leads to a high reservoir pressur, which results in a higher MMP value for immiscibility conditions. Meanwhile, all reservoir/fluid information collected from Turkey is from heavy to extremely heavy oil, in which the oil gravity is from 10.8 to 12 °API.

Table 2. Special cases for CO_2 immiscible flooding.

Country	Field	Start Date Year	Depth ft	Net Thickness ft	Permeability mD	MMP psi	Oil Viscosity cp	Temperature °F	References
USA	Ritchie	1968	2600	9	2750	-	195	126	[32]
USA	Paradis	1987	-	17	2000	1823	-	148	[36, 37]
USA	Lick Creek	1976	2550	8.6	1200	-	160	118	[38, 39]
China	Tuha	2013	5495.5	37	3.4	4322	22.3	113	[40]
Turkey	Bati Raman	1986	4300	213.5	55	-	600	150	[41, 42]
Turkey	Camurlu	1984	4264	197	351	-	705	116	[43]
Turkey	Ikiztepe	1997	4430	57.5	450	-	936	122	[44]
China	Yaoyingtai	2011	6627	18	1.9	3862	1.91	208	
Malyasia	Dulang	2002	4579	-	112	3230	0.2	215	
Hungary	Szank	1992	-	-	255	3626	5.2	235.4	[33]

Table 3. Applicability guidelines for CO_2 immiscible flooding based on reservoir/fluid, operation, and evaluation parameters.

Reservoir/fluid Parameters					
	Mean	Minimum	Median	Maximum	Standard Deviation
Porosity, %	22	8	23	33	7
Permeability, mD	407	1	253	2750	565
Depth, ft	4293	1400	4365	8500	1824
Net Thickness, ft	78	5	40	300	81
Reservoir Temperature, °F	141	82	131	235	37
Initial Oil Saturation, %	56	30	60	86	18
Oil Gravity, °API	20	11	17	39	8
Oil Viscosity, cp	136	0.2	17	936	232
Operation Parameter					
	Mean	Minimum	Median	Maximum	Standard Deviation
CO_2 Utlization, Bscf	25	0.1	4	353	82
Evaluation Parameters					
	Mean	Minimum	Median	Maximum	Standard Deviation
Enhanced Production Rate, bbl/d	1653	12	248	9640	2688
CO_2 Injection Efficiency, Mscf/stb	9	0.4	9	20	7
Oil Recovery Increased, %	8	5	7	13	3

Table 3 depicts the guidelines to provide suitable ranges for CO_2 immiscible flooding based on the projects collected, which consist of reservoir/fluid parameters, operation parameters, and evaluation parameters. For a new field, by having reservoir/fluid information, the applicability of the field for implementing CO_2 immiscible flooding could be determined based on the guildelines. If the field is a good candicate, economic problems will be evaluated. In this case, operation parameters and evaluation parameters could help give ideas about the amount of CO_2 to be injected, the expectations production rate enhancement, CO_2 injection effieciency, and oil recovery enhancement. However, prediction models are needed to accurately forcast the effects of CO_2 injection, which helps to better evaluate the applicability of projects.

Prediction Models

Even though CO_2 miscible flooding is a mature technology that is well understood in the oil industry and several prediction models have been built using neural networks [45], the study of CO_2 immiscible flooding is limited. Moreover, the applicability and prediction models are scarce. Based on the literature, some applicability guidelines have been studied in steam flooding [46], polymer flooding

[31], and gel treatment [47]. However, the application of these guidelines are not accurate since most of the studies yielded at the stage of reservoir parameter analysis without considering other valuable evaluation parameters that could better represent the economic efficiencies of the operations. For example, enhanced oil recovery helps to evaluate whether additional oil could be produced if a CO_2 immiscible technique is applied in the field, and CO_2 injection efficiency (Mscf/stb) provides the information about how much CO_2 needs to be injected for 1 stb of oil production.

To find the applicability of projects for further economic evaluation, prediction models are established for enhanced production rates, CO_2 injection efficiency, and enhanced oil recovery by implementing linear multiple regression and support vector machine (SVM) techniques. The purpose of using multiple regression is to reveal the relationships between independent prediction variables and the dependent variable. The SVM method was selected to compare the accuracy with multiple regression methods because SVM is an easy and reliable method for small data sets, which avoids the over-studied problem.

Since the raw data includes extremely dimensional reservoir/fluid, operation, and evaluation parameters, and only reservoir/fluid informations are available for new projects, feature selections are needed to eliminate unnecessary information to increase the accuracy. Spearman's correlation coefficient and the Pearson correlation coefficient methods were used to find the relationships between all parameters. Table 4 presents Spearman's and Pearson's correlation efficiency in reservoir/fluid information of area, porosity, permeability, depth, current reservoir pressure, net thickness, reservoir temperature, initial oil saturation, oil gravity, and oil viscosity. Results show that the reservoir area has redundant information with reservoir pressure and oil gravity. Depth and temperature are positively related to MMP because with the increase of depth, the reservoir pressures and temperatures are normally higher; therefore, a higher MMP is required for immiscibility. Also, oil gravity is highly related to oil viscosity because it is a function of density. After eliminating the redundant information, the independent variables were porosity, permeability, depth, thickness, temperature, initial oil saturation, and oil gravity, which are used in prediction models.

Table 4. Spearman's and Pearson's correlation coefficient. Data with a red border indicates that the paired parameters are dependent to each other.

	A	Ø	K	D	P	h	T	S_{oi}	MMP	API
Porosity, %	-0.27 -0.43									
Permeability, mD	0.19 -0.14	0.65 0.54								
Depth, ft	-0.06 -0.30	-0.29 -0.28	-0.24 -0.20							
Current Reservoir Pressure (psi)	0.30 0.89	-0.10 -0.69	0.02 0.07	0.71 0.67						
Net thickness, ft	-0.05 -0.10	0.12 0.17	0.24 -0.17	-0.18 -0.23	-0.41 -0.40					
Reservoir Temperature, F	0.03 -0.43	0.18 0.11	0.16 0.05	0.63 0.75	0.02 0.09	0.25 0.08				
Initial Oil Saturation, %	-0.55 -0.07	0.06 -0.01	-0.68 -0.46	-0.28 -0.20	-0.67 -0.82	0.67 0.39	-0.39 -0.36			
MMP (psi)	-0.03 -0.38	-0.15 -0.39	-0.14 -0.19	0.71 0.62	0.71 0.84	-0.06 -0.22	0.82 0.52	-0.39 -0.36		
Oil Gravity, API	0.60 0.55	0.16 0.08	0.02 0.02	-0.28 -0.33	-0.20 0.04	-0.45 -0.41	-0.15 -0.21	-0.44 -0.57	-0.20 -0.26	
Oil Viscosity, cp	-0.54 -0.24	0.13 -0.18	0.40 0.09	-0.19 0.00	-0.04 0.00	0.57 0.36	0.07 -0.01	-0.18 -0.08	-0.18 -0.21	-0.98 -0.68

Spearman's Rank
Pearson

Figures 4 to 6 demonstrate the effectiveness of each prediction model. The horizontal axis contains the actual values, and the vertical axis represents the predicted values from linear multiple regression and support vector machines. Both axes are in the same scale, and thus, data that lays on the diagonal line depicts that the value is accurately predicted.

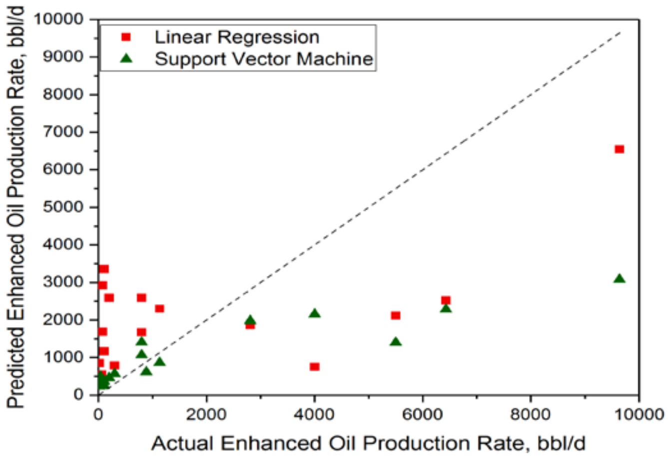

Figure 4. Comparison of linear multiple regression and SVM models for enhanced oil production rate.

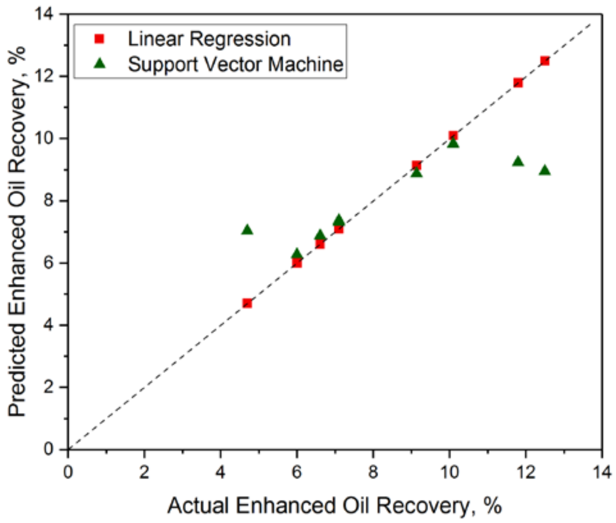

Figure 5. Comparison of linear multiple regression and SVM models for enhanced oil recovery.

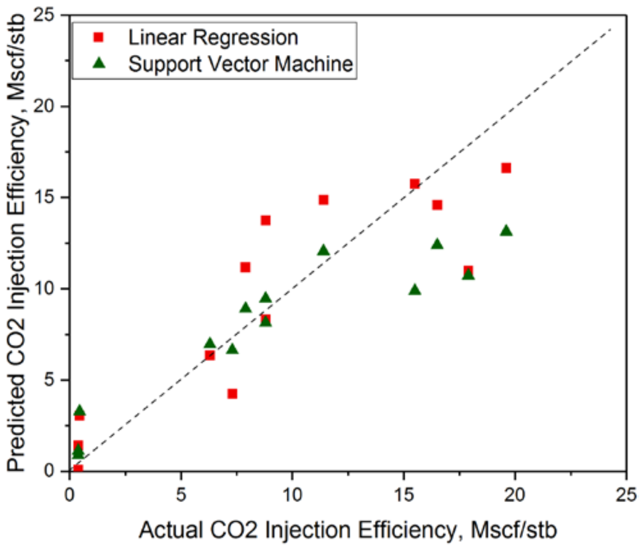

Figure 6. Comparison of linear multiple regression and SVM models for CO2 injection efficiency.

The root mean square error (RMSE) is calculated based on the prediction models, which is defined as the following:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)^2$$

$$\mathrm{RMSE} = \sqrt{MSE}$$

where $\widehat{Y_i}$ is the predicted value, and Y_i represents the original value.

Table 5 shows the accuracy of each model along with the number of data points used. Results indicate that the prediction model of enhanced oil recovery by implementing multiple regression is precise, where the RMSE is 0.00036, which means that this model has almost 100% accuracy. Also, high accuracies are found in models of CO_2 injection efficiency with both prediction methods. Prediction models for enhanced production rates are not as good compared with other models. The reason for this could be that the parameter is affected by the real operation conditions (e.g., well shut-in time, pressure, etc.), other parameters need to be used for the prediction of enhanced production.

Table 5. Root Mean Squared Error (RMSE) for Prediction Models.

	No. of Data Points	Multiple Regression	Support Vector Machine
Enhanced Oil Recovery	9	0.00036	1.67
CO_2 Injection Efficiency	13	3.1	3.436
Enhanced Production Rate	20	2069	2032

Conclusions

This paper provides a high-quality data set along with the establishment of applicability guidelines for CO_2 immiscible projects. Applicabilities are studied not only from the reservoir/fluid parameters, but also with the consideration of operation and evaluation parameters for the first time, where prediction models are implemented with multiple regression and support vector machine methods. To evaluate the applicability of CO_2 immiscible flooding for a new field project, reservoir/fluid guidelines were used for the first step, then the reservoir/fluid parameters could be fed into prediction models to forecast the usage of CO_2 injection and the incremental oil recovery. Based on these information, economic evaluation could be applied, which helps to make comprehensive decisions about inject CO_2 into the target reservoir.

Feature selection processing was conducted to avoid duplicate information and to help find the independent parameters, which were used in prediction models. The established prediction models show that support vector machines could predict the enhanced oil production rate and CO_2 injection efficiency better than multiple linear regression method, while the multiple linear regression method built an excellent model for the prediction of enhanced oil recovery with the RMSE close to 0.

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