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Prediction of Reducing Permeability due to Scale Deposition during Water-flooding Operations of Crude Reservoirs

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Abstract

Water-flooding is a necessity for improved extraction of crude from the existing reservoir. However, scale deposition is a challenge to be mitigated due to incompatibility among injected and formation water during water-flooding operations. Sulfates and carbonate scales of barium, calcium, and strontium are commonly encountered in diversified oil fields. Such scale deposition inside the pores of reservoir rock leads to a reduction in effective permeability, which ultimately affects the fluid flow and, thus, results in a decrease in overall productivity. Hence it is important to predict the impact of scale deposition on permeability reduction. In the present study, a generalized model using a multivariate regression approach was developed to estimate the reduction of permeability due to barium, calcium, and strontium sulfate scale deposition based on important variables, namely temperature, pressure, and brine concentration and pore volume injected. Experimental data of sulfate scale deposition in Malaysian sandstone reservoirs from published literature were utilized for modeling purposes. The developed simple generalized model can predict final permeability caused by scale deposition with good accuracy (<10 % relative error) compared to experimental data. Moreover, a sliding window regression approach was used to improve its performance. Models were subsequently validated using a new data-set of sandstone reservoirs available from open literature.

Keywords*: Scale deposition; Permeability reduction; Water flooding; Multivariate regression; Sliding window technique.*

1. Introduction

The growth in demand for energy across the world and consequent surges in oil prices necessitate increased production of crude oil in an efficient and economical manner. Worldwide oil recovery from conventional primary methods generally falls in the range of 5 – 15 % of original oil in place (OOIP), which is mostly supplemented by secondary methods contributing to additional 30% recovery benefits [1]. Waterflooding is the oldest and widely used secondary recovery technique to recover remaining oil from depleting reservoirs due to easy access to the produced water and ease of its injection. It requires less capital and operating cost compared to other expensive enhanced oil recovery methods such as chemical injection, gas injection, steam injection, and polymer flooding [2]. Basically, waterflooding operations involve the injection of water into the reservoir to displace the oil through interconnected porous structures. However, scale deposition is one of the critical issues to be dealt with during water flooding operations. Incompatibility between formation and injected water results in scale formation and subsequent reduction in reservoir permeability due to blockage of the rock pore spaces. Permeability is a key factor governing the efficiency of oil recovery; however, the permeability of the reservoir gets declines due to the ongoing scale formation, leading to a substantial reduction in overall recovery from the reservoir.

Incompatibility of water used for injection and the temperature and pressure conditions of the subsurface reservoir are major influencing factors for scale formation [3]. A typical example of incompatible water is a combination of injected sea water along with the reservoir formation water. Injection water (sea water) generally rich in sulfate ion (SO_4^{-2} ion) when mixed with formation water (produced water) consisting of high concentrations of calcium, barium or strontium ions (Ca^{+2}, Ba^{+2} and Sr^{+2}) leading to formation of insoluble calcium sulfate, barium sulfate and strontium sulfates ($CaSO_4$, $BaSO_4$ and $SrSO_4$) which are getting precipitated and are deposited as scales in and thereby reducing the porous nature of the reservoir rocks. However, calcium carbonate scale being deposited due to decomposition of calcium bicarbonate resulting due to reduction in reservoir pressure during primary recovery (crude along with water cut are drawn to the surface facilities thereby releasing the excess pressure inside the reservoir). Such decomposition precipitates the calcium carbonate inside the surface production equipment and thus, contributes to equipment wear and corrosion [4]. Other types of scales have been also precipitated in oil fields such as iron, zinc and lead sulfide [5].

In published literature, several researchers have studied scale deposition in the laboratory using either packed glass beads and sands [6-7] or core plugs [8-10]. Some of these studies focused on single mineral scale deposition while some are on composite scale precipitation. Along with laboratory experiments, some of the researchers have developed theoretical models or empirical models or machine learning or ANN methods for estimation of permeability reduction due to scale deposition [11-13].

Todd and Yuan [5] have carried out laboratory core-flood to study scale precipitation of barium and strontium sulfate using North Sea water and two formation water at elevated temperature to simulate the field scale conditions. Their experimental results demonstrated that permeability reduction at elevated temperature ranged from 12 to 93 % of initial core permeability depending on brine composition, initial permeability and brine injection period. They have developed a model based on Pitzer equation for prediction of barium and strontium sulfate precipitation. Their study is limited to precipitation only and calcium sulfate scale is not covered by the model. McElhiney *et al.* [8] have studied barium sulfate precipitation using core-flood experimental set up of Berea sandstone cores at ambient temperature and pressure. They have conducted the experiments using synthetic raw sea water containing high and low concentration of sulfate ions (2860 ppm and 36 ppm) which was mixed with formation water containing barium ions (240 ppm). They concluded that potential for scaling is strongly dependent on mineral concentration. However, the study is limited to the experimental data for barium sulfate scale deposition only. Moghadasi *et al.* [6, 14-15] have investigated formation damage due to scale deposition in Iranian oil fields. They have reported that loss of water injection in the Siri field in Iran from an initial injection rate of 9100 bbl./day to 2200 bbl./day within six years of waterflooding operations [14]. They indicated that loss of injectivity was the result of permeability reduction caused by scale deposition in the pores. Moghadasi et al.[15] have suggested a predictive model for calcium sulfate scale deposition in Iranian oil field by mixing incompatible waters due to thermodynamic, kinetic and hydrodynamic changes. They have analyzed scale formation in terms of Saturation index and scaling tendency and developed a relevant model. The main drawback of this model was that, Saturation index only allows qualitatively assessing the ability of the water to precipitate or dissolve the salt rather than prediction of permeability reduction as a result of scale formation. Moghadasi *et al.* [6] have performed an experimental study of permeability reduction due to calcium carbonate and calcium sulfate deposition using packing material of sand and glass beads of particle size in the range of 180 – 1000 μm and at different temperature of 50 – 80°C and flow rates of 25 – 100 cm^3/min. They have used three synthetic brine samples having varied calcium, sulfate and carbonate concentrations. Their study indicated that both the flow rate and temperature have detrimental effects on the permeability reduction due to both calcium sulfate and carbonate scale depositions. They have developed a simple empirical correlation between flow rate, initial permeability and the reduction of permeability with time based on experimental data. Their study focused mainly on mechanism of calcium sulfate and carbonate scale depositions and inclusion of effects of initial permeability and flow velocity to the model development which is applicable to calcium sulfate and carbonate scale depositions only.

Abu-Khamsin and Ahmed [9] have performed laboratory core flooding experiments to study the calcium sulfate precipitation in Berea sandstone using synthetic brine containing calcium and sulfate ions. They have developed and validated a general reaction rate equation based on theoretical approach to predict calcium sulfate deposition for a given temperature, brine concentrations and flooding velocity using experimental data and reported that temperature and flooding velocity has significant effect as compared to pressure. However, the model only covers calcium sulfate deposition. The laboratory experiments to examine the effect of temperature, pressure and concentrations of barium, calcium, strontium and sulfate ions on scale formation in Malaysian Berea sandstone of 12.3 – 13.84 mD permeability were conductedby Merdhah [4], he has used synthetic formation water containing high and low barium ion concentration (2200 ppm and 250 ppm), and Angsi sea water containing sulfate ion concentration (2750 ppm) and at different temperature and pressure. Based on experimental results it was reported that the permeability decreased from 13 – 19% of initial permeability at high barium ion concentration and from 5 – 9 % of initial permeability at normal barium ion concentrations. It was also reported that temperature, differential pressure and concentration of mineral ions have major effects on the permeability impairment.

Ghaderi *et al.* [16] have conducted series of experiments to investigate the effect of different parameters on calcium sulfate precipitation such as concentration of mixing brines, pressure, and flow rate using a glass micromodel as porous medium. Their results indicated that increase in temperature, brine concentration, and flow rate causes the increased scaling tendency, however, the pressure has a minor effect. They have developed dimensionless correlation which incorporated permeability reduction as an exponential function of three parameters namely pore volume injected, Reynolds number, and super saturation index. Subsequently they have determined the adjustable parameters using Genetic Algorithm Optimization technique. They validated the model with experimental core data with a mean absolute error of 11.16 %. Shortcomingof the model is its applicability to unconsolidated porous media alone.

Tahmasebi *et al.* [7] have conducted the theoretical and experimental study to investigate permeability reduction due to calcium sulfate scale deposition. The experimental runs were conducted in packed column with glass bed packing and carbonate grain packing of average size 200 µm. They have developed a complex model for prediction of permeability reduction as a function of temperature, super saturation index, surface properties empirical constants, initial porosity and volumetric flow rate to predict permeability reduction and proposed model validated with Berea sandstone core data at different temperature and flow rate values and varying concentrations of calcium and sulfate ions. The developed model is limited to prediction of permeability reduction due to single scale deposition of calcium sulfate only though it includes a large number of process parameters. Hajirezaie *et al.* [17] have developed two predictive models for permeability reduction in porous media due to barium sulfate scale using multivariate regression analysis based on published literature data. The main limitation of their models is that they have reported two different models and their coefficients are varying for high (2200 ppm) and low barium concentrations (250 ppm).

From the previous literature studies, it can be observed that most of the scaling or permeability reduction models are based on either conventional kinetic or thermodynamic or hydrodynamic approach or ANN or machine learning based approaches which are highly complex and requiring huge computational framework along-with sufficient expertise into these areas. Another shortcoming of the previous studies is that they have not incorporated all the important process variables affecting the scale deposition and most of these models predict permeability reduction due to single scale deposition (e.g. $CaSO_4$) only. Additionally, different models were developed for different scales and even for different concentration ranges. Lastly, laboratory core flooding experimental studies of permeability reduction due to scale deposition necessitates sophisticated instruments and the whole process of core preparation and experimentation is time consuming and expensive. Hence, in this study the primary focus is on development of a generalized simple mathematical model which can predict permeability reduction considering all possible influencing operating parameters and hopefully will able to replace the expensive and extensive laboratory testing with a minimal computer resources.

2. Model development for prediction of permeability reduction due to scale deposition during water flooding process

The development of mathematical model to predict permeability reduction in porous reservoir rock matrix due to mineral scale deposition during water injection process is essential in petroleum industry for successful implementation of such recovery process. In this study, models utilizing multivariate regression analysis were developed based on experimental data reported in literature [4, 10]. The reservoir rock formation used in their study was Malaysian sandstone core with an average porosity of 32% and permeability ranges from 12.30 – 13.84mD. In the original experimental data of published literature [4, 10], synthetic formation water containing high and low barium concentrations, salinity water having high and low calcium and strontium ions and seawater containing sulfate ions were used. Table 1 represents the detailed description of experimental data sets comprised of 36 different process conditions with five varying input parameters used in this study.

Table 1. Experimental conditions of Merdhah and Yassin [4, 10]

Input Variables	Values
Initial permeability (mD)	12.3-13.84
Temperature (K)	323, 343, 353
Pressure (psig)	100, 150, 200
Brine concentration (mg/L)	Barium = 2200, 250
	Calcium = 30000, 7000
	Strontium = 1100,500
	Sulfate = 2855
Pore volume injected	2 - 83 pore volumes

Initial permeability, temperature, pressure, pore volume injected and brine concentrations are the important input parameters that have strong effect on final permeability of the reservoir matrix resulting from scale deposition. A simple mathematical model relating final permeability (a targeted output) as a function of five input parameters as initial permeability, temperature, pressure, pore volume injected and brine mineral concentration was developed.

The following generalized multivariable nonlinear model is targeted:

$$K_d = a \times K_i^b \times T^c \times PV^d \times [(Ca^{+2} + Ba^{+2} + Sr^{+2}) \times (SO_4^{-2})]^e \times P^f \quad (1)$$

where: K_d: final permeability in milidarcy (mD); K_i: initial permeability in milidarcy (mD);.T: Temperature in (K); P: Pressure in psig; PV: Pore volume injected (–); Ca^{+2}, Ba^{+2}, Sr^{+2},SO_4^{-2}: Concentration of calcium, barium, strontium and sulfate ions in mg/L.

Initially, a six-parameter non-linear model (Eqn. 1) was developed to predict the permeability reduction due to scale deposition process. The model was later modified by considering only five parameters. Five parameter model was developed in a same form of multivariable non-linear model as mentioned below:

$$K_d = K_i^a \times T^b \times PV^c \times [(Ca^{+2} + Ba^{+2} + Sr^{+2}) \times (SO_4^{-2})]^d \times P^e \quad (2)$$

The constant parameter of earlier six parameter model is dropped for brevity in the five parameter model represented by Eqn. 2. The optimal parameters *a*, *b*, *c*, *d*, *e* and *f* of the proposed models (Eqns. 1 and 2) were found using two approaches namely, multivariate regression analysis in EXCEL and multivariable optimization technique in MATLAB environment. To assess the efficiency and accuracy of the developed regression based models, two statistical parameters namely percentage relative error and coefficient of determination were utilized.

2.1. Description of multivariate regression approach

Multivariate regression is a standard statistical method used to estimate the relationship between the one dependent variable of interest (also known as response variable, i.e., the targeted output) and multiple independent variables (called as predictor variables).

The multivariate regression model can be written in the general form as

$$Y = \beta_0 + \beta_1 X_1 \pm \ldots + \beta_i X_k + \varepsilon \quad (3)$$

where, Y represents the experimental outputs (K_d), X_i represents the experimental inputs (K_i, T, PV, Brine Conc., P); β_i's are the coefficients of the proposed model (i = 1, 2, …, n) and ε stands for the residuals (errors) between model predictions and corresponding experimental values.

In multivariate analysis, the optimal parameters for the model that best fit the data points are estimated using least square method that minimizes the square of residuals (SSR).

$$SSR = \sum_{i=1}^{n} \varepsilon_i^2 = \sum_{i=1}^{n} \left(Y_i - \beta_0 - \sum_{j=1}^{k} \beta_j X_{ij}\right)^2 \quad (4)$$

In this study, the present non-linear models (Eqns. 1 and 2) was converted to linear form using logarithms and then model parameters were found using multivariate regression method in EXCEL.

2.2. Description of multivariable optimization technique using Nelder–Mead simplex algorithm approach

The Nelder – Mead Simplex method was proposed by Nelder and Mead in 1965 [18]. This technique is used for finding local minimum for function of 'n' variables applied to nonlinear optimization. The algorithm of this method uses comparison of function value at the 'n+1' vertices of a geometrical shape, which is also called as Simplex. For two variables, a simplex is a triangle and the method is a pattern search that evaluates and compares function values $f(x, y)$ at the three vertices of a simplex. The worst vertex, where function value is highest, is rejected and replaced with a new vertex which is found by reflecting away from the worst point about the axis formed by the other vertices. A new triangle is formed and the search is continued. The process generates a sequence of triangles (which might have different shapes), for which the function values at the vertices get smaller and smaller and the coordinates of the minimum point are found. Lastly, the objective function of the best point is considered as the optimum. This method is very effective and computationally compact [18-19].

2.3. Statistical error analysis

In order to measure the efficiency and accuracy of the developed model, two statistical methods were utilized such as percentage relative error and coefficient of determination [12, 17].

1. Percentage relative error or percentage error: it is measure of the relative deviation of predicted reduced permeability from the experimental value.

$$E_i = \left(\frac{(K_d)_{Pred.} - (K_d)_{expt.}}{(K_d)_{expt.}}\right) \times 100, i = 1, 2, \ldots, n \quad (5)$$

2. Coefficient of determination: This parameter is measure of how well is the model predicted value is close to actual experimental value. If this parameter is close to unity means model is fitted well to experimental values.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} [(K_d)_{Pred.} - (K_d)_{expt.}]^2}{\sum_{i=1}^{n} [(K_d)_{Pred.} - \overline{(K_d)}_{expt.}]^2} \quad (6)$$

3. Results and discussion

The developed generalized models were utilized to predict the permeability reduction due to scale formation as a result of incompatibility of injected and formation water (produced water) during secondary oil recovery. The optimal parameters of two non-linear models (six parameter model as Eqn. 1and five parameter model as Eqn. 2) were estimated by two techniques namely multivariate regression using EXCEL and multivariable optimization using MATLAB based on experimental data from published literature [4, 10] and are listed in Table 2.

It is clearly evident that coefficients of both five and six parameter models estimated using multivariate regression are identical to parameters obtained through multivariable Simplex optimizer.

The overall six parameter models obtained by multivariate regression EXCEL and multivariable optimization done in MATLAB are represented by Eqns. 7 and 8 as follows:

$$K_d = 0.8580 \times K_i^{0.8543} \times T^{0.1197} \times PV^{-0.0533} \times [(Ca^{+2} + Ba^{+2} + Sr^{+2}) \times SO_4^{-2})]^{-0.0126} \times P^{0.0222} \quad (7)$$

$$K_d = 0.7969 \times K_i^{0.8609} \times T^{0.1274} \times PV^{-0.0516} \times [(Ca^{+2} + Ba^{+2} + Sr^{+2}) \times (SO_4^{-2})]^{-0.0121} \times P^{0.0219} \quad (8)$$

Similarly, five parameter model equations are represented by following expressions (Eqn. 9 using EXCEL and Eqn. 10 using MATLAB):

$$K_d = K_i^{0.8452} \times T^{0.09791} \times PV^{-0.05299} \times [(Ca^{+2} + Ba^{+2} + Sr^{+2}) \times (SO_4^{-2})]^{-0.0126} \times P^{0.02157} \quad (9)$$

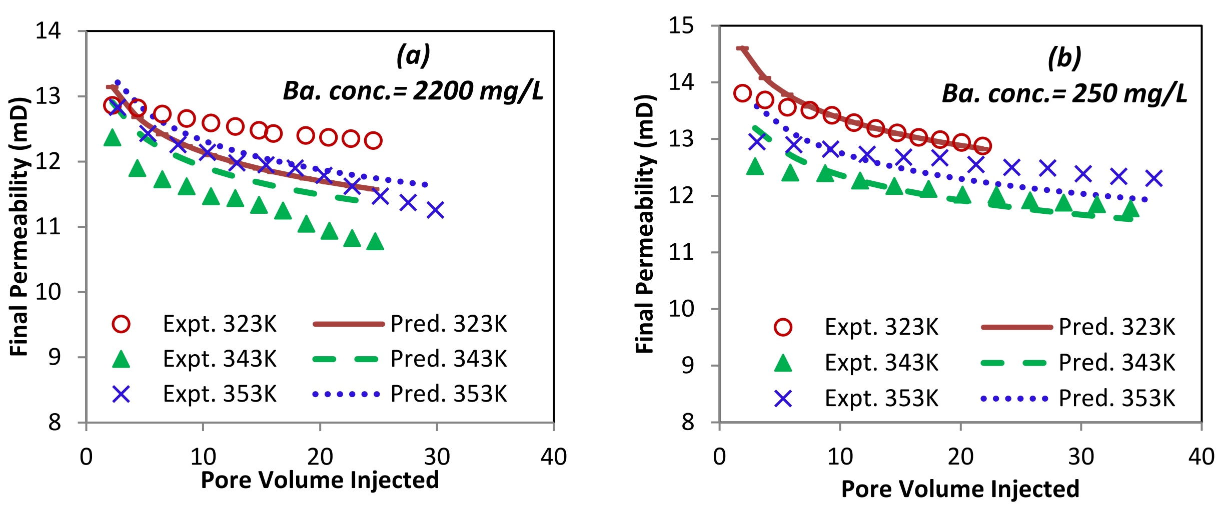
$$K_d = K_i^{0.8465} \times T^{0.0954} \times PV^{-0.0512} \times [(Ca^{+2} + Ba^{+2} + Sr^{+2}) \times (SO_4^{-2})]^{-0.0121} \times P^{0.0210} \quad (10)$$

Table 2. Model coefficients estimated using multivariate regression using EXCEL and multivariable optimization using MATLAB (Eqns. 7, 8, 9 and 10)

Model coefficients	Multivariate regression using EXCEL (Eqn. 7)	Multivariable optimization using MATLAB (Eqn. 8)	Model coefficients	Multivariate regression using EXCEL (Eqn. 9)	Multivariable optimization using MATLAB (Eqn. 10)
a	0.8580	0.7969	--	--	--
b	0.8543	0.8609	*a*	0.8452	0.8465
c	0.1197	0.1274	*b*	0.09791	0.0954
d	- 0.0533	- 0.0516	*c*	- 0.05299	- 0.0512
e	- 0.0126	- 0.0121	*d*	- 0.0126	- 0.0121
f	0.0222	0.0219	*e*	0.02157	0.0210

In Fig. 1, the model prediction of final permeability (using Eqn. 9) due to barium, strontium and calcium sulfate scale deposition are compared with experimental data of published literature [4,10] at different temperature (323 to 353 K) for high and low concentrations of barium, strontium and calcium ions. It can be seen that predicted values of final permeability using multivariate regression using EXCEL exhibits good agreement with experimental findings [4,10]. Similarly, the predicted final permeability (using Eqn. 10) utilizing MATLAB are reported in Fig. 2 and compared with earlier published results. As evident from Fig. 2, the multivariable optimization MATLAB based model can predict the final permeability quite accurately.

Furthermore, to quantify the efficiency and accuracy of the developed models, percentage relative error and coefficient of determination (using Eqns. 5 and 6) were calculated for all the predictions and the obtained values are provided in Table 3. It is observed that the five-parameter model obtained using MATLAB, predicts the final permeability with accuracy of 90.13%, whereas accuracy for six parameter model is 89.97 %. Similarly, accuracy of five parameter model expression obtained using Excel is 90.56 % and 90.46 % for six parameter model. Our results revealed higher accuracy of prediction using developed simple generalized models as compared to accuracy of previously developed models of Gandheri *et al.* [16] utilizing Genetic Algorithm Optimization technique of 88.84 % and Ahmadi *et al.* [13] employing Genetic algorithm-least squares support vector machine (GA-LSSVM) and Artificial Neural Network (ANN) of 85 %.



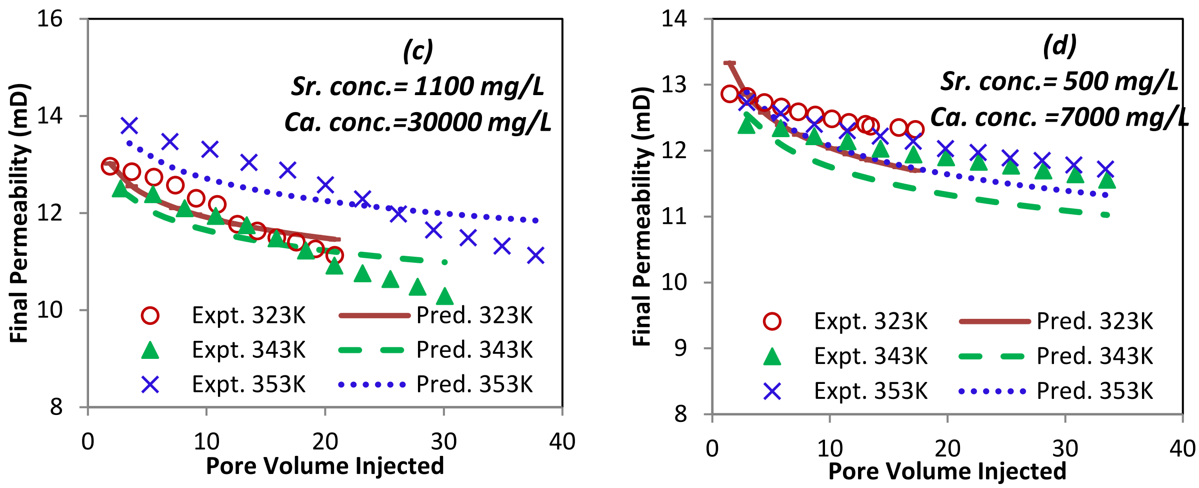


Fig. 1. Model predicted (using Eqn. 9) and Experimental Final permeability [4,10] versus Pore volume injected data at different temperature due to barium, strontium and calcium sulfate scale formation (*a*) High barium concentration 2200 mg/L, (*b*) low barium concentration 250 mg/L, (*c*) High strontium concentration 1100 mg/L with calcium concentration of 30000 mg/L and (*d*) low strontium concentration 500 mg/L with calcium concentration of 7000 mg/L

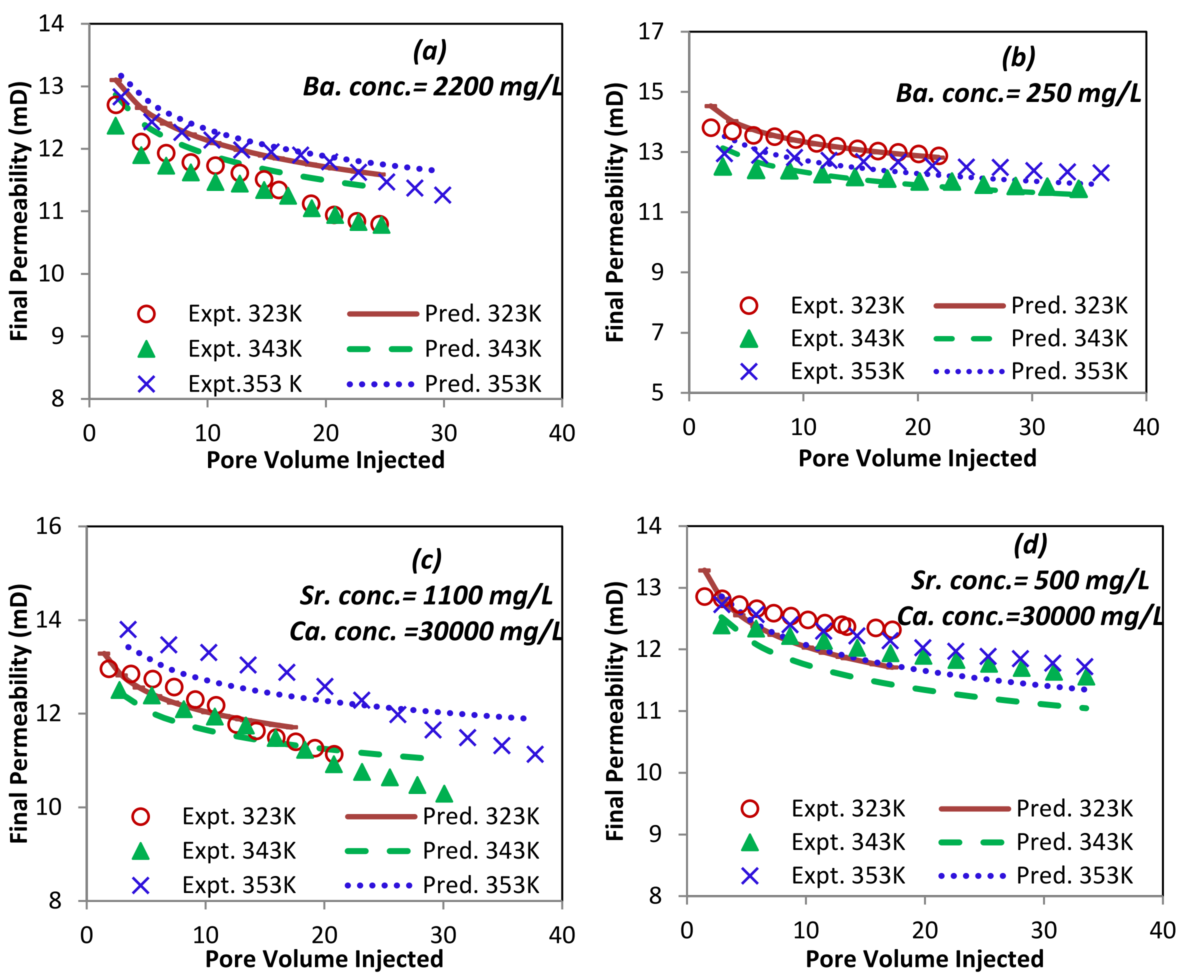


Fig. 2. Model predicted (using Eqn. 10) and Experimental Final permeability [4,10] versus Pore volume injected data at different temperature due to barium, strontium and calcium sulfate scale formation (*a*) High barium concentration 2200 mg/L, (*b*) low barium concentration 250 mg/L, (*c*) High strontium concentration 1100 mg/L with calcium concentration of 30000 mg/L and (*d*) low strontium concentration 500 mg/L with calcium concentration of 7000 mg/L.

Table 3. Percentage relative error and coefficient of determination of five and six parameter model

Model	Relative percentage error [E_i]		Coefficient of determination [R^2]	
	Matlab (Eqn. 8 and 10)	Excel (Eqn. 7 and 9)	Matlab (Eqn. 8 and 10)	Excel (Eqn. 7 and 9)
6 parameter	10.03	9.57	0.673	0.687
5 parameter	9.87	9.44	0.669	0.684

It clearly indicates that the obtained accuracy of both five and six parameter models as well as the coefficient of determination value (R^2) using multivariate regression EXCEL approach is also comparable with MATLAB based simplex optimizer model.

Additionally, to investigate the effect of each parameter on permeability reduction, a relevancy factor was calculated [17]. It signifies the effect of input parameter on output parameter. A bigger value of relevancy factor indicates greater impact of input parameter on output function. It is defined as follows:

$$R_V(IP_k, K_{di,}) = \frac{\sum_{i=1}^{n}(IP_{k,i} - IP_{k,avg.})\times(K_{d,Pred.i} - K_{d,pred.avg})}{\sqrt{\sum_{i=1}^{n}[IP_{k,i} - IP_{k,avg.}]^2 \times \sum_{i=1}^{n}[(K_d)_{pred.,i} - (K_d)_{Pred.,avg.}]^2}} \qquad (11)$$

where: $K_{d,Pred.i}$, $K_{d,Pred.avg}$: i^{th} and average value of predicted permeability; $IP_{,k.i}$, $IP_{,k.avg}$: i^{th} and average value of k^{th} input parameter (initial permeability, temperature, pressure, pore volume injected, brine concentration).

The results of calculation of relevancy factor are presented in Fig. 3. As depicted in Figure, the initial permeability, brine concentration and pore volume injected are the important influential parameters as compared to others and they contribute more to the final permeability reduction due to the scale deposition. This signifies that permeability reduction by scale deposition can be regulated by controlling volumetric flow rate of injecting fluid and brine concentration as initial permeability is inherent flow property of the reservoir rock. In addition, it has been observed that temperature and pressure are least influencing parameters as compared to other three factors. Similar findings were also reported in previous studies of scale deposition of calcium sulfate and barium sulfate based on their experimental data and model predictions [9,17].

Furthermore, the developed regression based models are validated utilizing new set of experimental data for sandstone reservoir for calcium sulfate scale deposition [20].

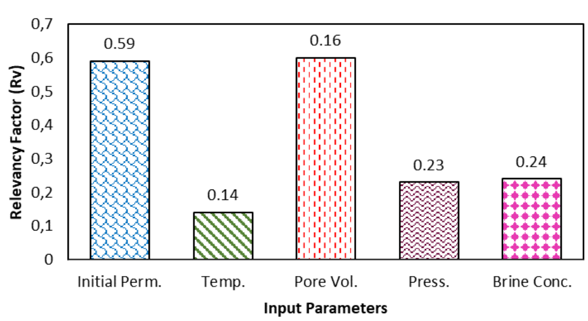


Fig. 3. Relevancy factor versus five input parameters contributing scale deposition

3.1. Validation of model

In order to verify the validity of the developed model, 28 experimental data points for permeability reduction of sandstone core samples due to calcium sulfate scale formation of Haghtalab *et al.* [20] were utilized. They had reported the core flooding experiments using sandstone core sample having initial permeability of 37.9 mD and porosity of 16.45 % and injecting two synthetic brine water which were represented as formation and injection water.

The formation water was rich in calcium ion (21240 mg/L) whereas injection water was rich in sulfate ion (4224 mg/L). The operating temperature was of 25˚C and injection rates of 12 and 18 cm^3/hr. As both model Eqns. 9 and 10 showed identical results, the developed model (Eqn. 10) was utilized to predict the final permeability due to calcium sulfate scale deposition and then it has been plotted along with experimental data at different injection rates for comparison in Fig. 4*a* and *b*. As depicted in figure, the prediction of developed model is in good agreement with the experimental data with 78.38% and 91.26 % accuracy for 12cm^3/hr. and 18 cm^3/hr. injection rate respectively. It is observed that for pore volume injected up to 5 units, percentage permeability reduction is higher i.e. 35% at 12 cm^3/hr., whereas it was only 20 % for higher flow rate of 18 cm^3/hr. A plausible mechanism may be initial scale deposition in porous media is dependent on initial nucleation which is followed by enhanced rate of ionic precipitation due to faster crystal growth. At higher injection rate of 18cm^3/hr., significant flow shearing forces controls the further crystal growth which results in less reduction in permeability. In contrast, at lower injection rate of 12 cm^3/hr., impact of shearing force is less on crystal growth, hence higher amount of crystals can be deposited leading to more blockage of pores and subsequently higher reduction in permeability as observed. As the developed models are based on concentrations of scaling ions, more deviation is observed between experimental and predicted data points for lower injection rate (Fig. 4*a*). Similar findings were reported by Todd and Yuan [5] based on experimental study of scale precipitation. The analysis indicates that injection flow rate and thus volume of injected fluid does have significant effect on permeability reduction due to scale deposition. So, it is evident that the developed simple generalized models can reasonably predict and monitor permeability reduction due to scale deposition during water flooding operation for varied range of process parameters.

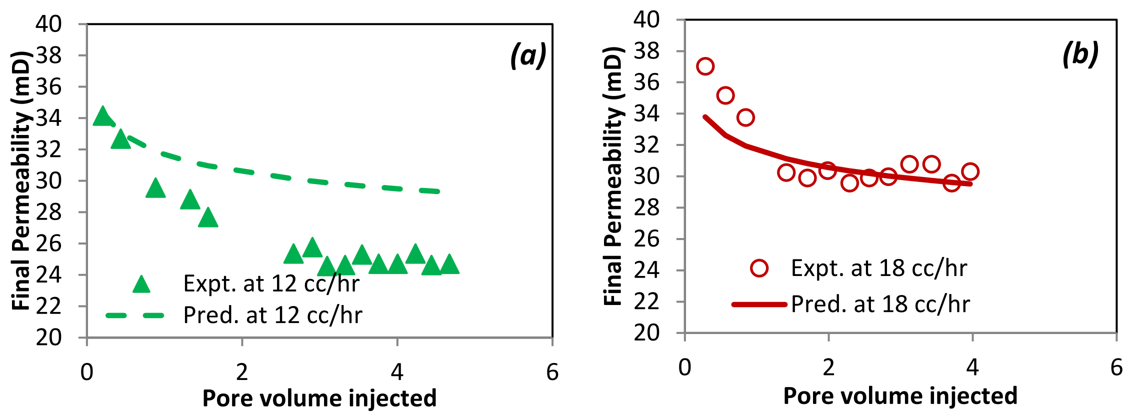


Fig. 4. Comparison of measured permeability data of Haghtalab *et al.* [20] with model predicted permeability (*a*) 12 cm^3/hr.(*b*)18 cm^3/hr

3.2. Modified model using Sliding Window regression approach

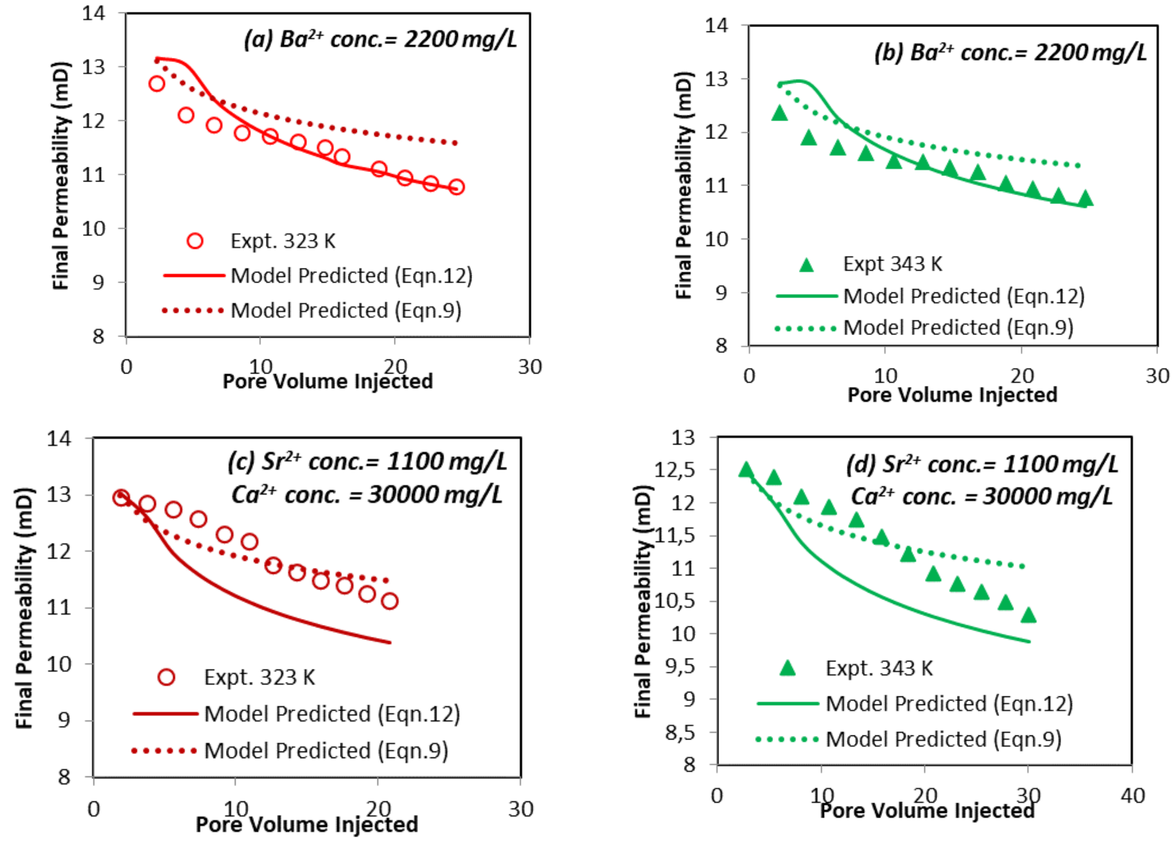
In this study, in order to improve the performance of developed models to predict permeability reduction due to scale deposition, the sliding window regression approach was employed for the similar previous literature experimental data [4,10]. Sliding window approach utilizes a model to predict present output value (Y_P) of variable based on prior step value (Y_{P-1}). The number of previous steps is called the window width. Earlier reported five parameter EXCEL based regression model and MATLAB based simplex optimizer models were modified using sliding window approach with one step window width. Hence, modified five parameter models based on sliding window approach uses the relationship of final permeability as a function of its own one step previously predicted value instead of using initial permeability before deposition occurs.

Hence, the new modified models are represented as:

$$K_{d,P} = K_{d,P-1}^{0.8452} \times T^{0.09791} \times PV^{-0.05299} \times [(Ca^{+2} + Ba^{+2} + Sr^{+2}) \times (SO_4^{-2})]^{-0.0126} \times P^{0.02157} \quad (12)$$

$$K_{d,P} = K_{d,P-1}^{0.8465} \times T^{0.0954} \times PV^{-0.0512} \times [(Ca^{+2} + Ba^{+2} + Sr^{+2}) \times (SO_4^{-2})]^{-0.0121} \times P^{0.0210} \quad (13)$$

It is observed that the modified five-parameter EXCEL and MATLAB based model expressions obtained (Eqns. 12 and 13) could fit the experimental data of 432 different values of Merdhah, [4] and Merdhah and Yassin, [10] with overall better accuracy. As representative cases, Fig. 5 (*a*, *b*, *c*, *d* and *e*) depicts the comparison between the obtained results of modified model utilizing sliding window approach using Excel (Eqn. 12) and our previous Excel based regression model (Eqn. 9) along with corresponding experimental training as well as validation data. As indicated from Fig. 5*e* the prediction of modified model matches well with experimental data as compared to previous model. As can be seen from Fig. 5, the improved model (Eqn. 12) results follows the trend of measured experimental permeability reduction data as compared to previous model (Eqn. 9) and close agreement was found with experimental findings.



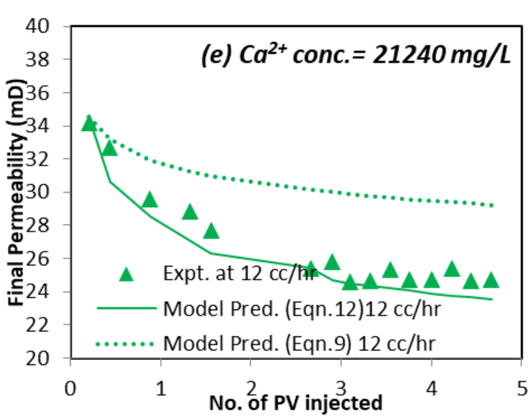


Fig. 5. Comparison of final permeability estimated using modified Model (Eqn. 12), previous model (Eqn. 9) and Experimental final permeability [4,10] for barium, strontium and calcium sulfate scale deposition(a) High barium concentration 2200 mg/L at 323 K, (b) High barium concentration 2200 mg/l at 343 K, (c) High strontium concentration 1100 mg/L and calcium 30000 mg/L at 323 K and (d) High strontium concentration 1100 mg/L and calcium 30000 mg/L at 343 K and (e) Calcium concentration 21240 mg/l and sulfate concentration 4224 mg/l at 12 cm3/hr. [20]

4. Conclusion

The generalized, simple models were developed using EXCEL multivariate regression analysis and MATLAB multivariable optimization technique for the prediction of the permeability reduction due to scale deposition during water flooding process at five important process parameters namely temperature, pressure, concentration of scaling ions (e.g. Ca^{+2}, Ba^{+2}, SO_4^{-2} etc.) and pore volume injected based on experimental data available in literature. These models were enhanced by utilizing sliding window regression approach. The efficacy of the model was validated with a wide range of experimental data from published literature. The developed regression based models are able to predict final reduced permeability due to scale deposition of barium, strontium and calcium sulfate with relative percentage error of less than 10%. Analysis of relative input parameter impact indicates effect of brine concentration and flooding velocity on permeability reduction is higher than that of other parameters. Therefore, proposed simple generalized models are proved reasonably accurate for prediction of final permeability for various scale deposition inclusive of all possible influencing process parameters. This type of model can be used as soft sensors as it can predict the reservoir permeability beforehand and input parameters can further be tuned in order to maintain the desired permeability in the rock matrix for an efficient flow for longer period.

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