applied random forest lswi

by Fiki Hidayat

Submission date: 30-Mar-2023 10:11PM (UTC+0700)
Submission ID: 2051075861
File name: Applied_Random_Forest_LSWI.pdf (1.78M)
Word count: 6387
Character count: 34244

Alexandria Engineering Journal (2022) 61, 2408–2417

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Applied random forest for parameter sensitivity of low salinity water Injection (LSWI) implementation on carbonate reservoir

Fiki Hidayat *, **T. Mhd. Sofyan Astsauri**

Department of Petroleum Engineering, Universitas Islam Riau, Jl. Kaharuddin Nasution No 113, Pemberhentian Marpoyan, Pekanbaru 28284, Indonesia

Received 14 April 2021; revised 20 June 2021; accepted 25 June 2021
Available online 10 July 2021

KEYWORDS

Low salinity water injection (LSWI);
Carbonate Reservoir;
Sensitivity Analysis;
Random Forest Algorithm

Abstract This study applied a Machine Learning Algorithm based on Random Forest Regression for eliminating the insignificant parameter and evaluating the correlation between each parameter and response parameter on the LSWI process. 1000 experimental designs of LSWI parameters, Reservoir & Injection Temperature, Volume Injection, Formation Water Composition, and Injection Water Composition were build using Design of Experiment on CMOST from Computer Modeling Group with Recovery Factor as the response parameter. Finally, the sensitivity analysis is carried out on Random Forest Regressor based on the decrease in the mean squared error (MSE). The Random Forest Algorithm methods respectively recognized Injection $SO4^{2-}$ Composition, Formation Water $SO4^{2-}$ Composition dan Volume Injection as the top three of most significant parameters. Five variations of the random state value are applied and the hyperparameters of Random Forest also optimized. Both training and test data, the R^2 score respectively are consistently over 0.9 for 5 variations of the random state used. The information about the significant operation parameter of the LSWI process presented in this article is potential bearing the novel to the industry. The insight into those parameters is predicted to be useful to encourage the LSWI implementation on Carbonate Reservoir.

1. Introduction

There are many numbers of energy types in the world, but the main source of energy used comes from fossil energy, crude oil and natural gas. In line with the level of thirst for energy which is predicted to increase by 50% in 2050, oil and gas and other types of fossil energy will still contribute at least 50% of the total energy needed in the future [26]. Hence, it is very important to find and study methods that can streamline the acqui-

* Corresponding author.
E-mail addresses: fikihidayat@eng.uir.ac.id (F. Hidayat), tengkusofyan41@gmail.com (T. Mhd. Sofyan Astsauri).

Peer review under responsibility of Faculty of Engineering, Alexandria University.

https://doi.org/10.1016/j.aej.2021.06.096

sition/production of fossil energy, especially crude oil and natural gas.

Low Salinity Water Injection (LSWI) had been considered as a potential method to be used as an Enhanced Oil Recovery method after Morrow and his friends, [25,38,39,43], concluded based on their research that oil recovery depends on the composition of the injection water. The popularity of LSWI in increasing oil recovery is growing rapidly due to its efficiency in moving oil from light to medium gravity crude oil, easily injected into formations, the abundant source of water and its affordability and low capital and operating costs [5].

Adegbite et al. [1] expressed that the carbonate reservoir is estimated to cover up to 60% of the world's total oil and gas reserves. Regrettably, only a single reported LSWI field project on the carbonate reservoir. The success of LSWI in increasing oil recovery in carbonate reservoirs has been widely described in many publications. Unfortunately, this success is still on a laboratory scale and only one LSWI pilot test was recorded up to this time which reported by Yousef and his colleagues in 2012 [31]. The existed challenges in the carbonate reservoir such as high level of heterogeneity, the high energy bond between the carbonate surface and polar component crude oil and the fact that almost 90% of carbonate rocks are in neutral or oil-wet condition resulting in a very low primary recovery (30% on average), driving to the difficulty of analyzing the effect of LSWI on this type of reservoir [16,27].

Based on the conducted laboratory experiments, several operating parameters affected oil recovery during the LSWI process. Adegbite et al. [1], Al-Attar et al. [2], Awolayo et al. [12], Derkani et al. [16], Egbe et al. (2020), R. Gupta et al. [20], Høgnesen et al. [24], Strand et al. [37], Webb et al. [41] and Y. Zhang & Sarma [48] concluded from their laboratory experiment that sulfate ion is an active ion in changing the wettability of carbonate rock during LSWI process which led to the increase of oil recovery. Beside, Chandrasekhar et al. [14], Shehata et al. [35] and P. Zhang et al. [47] proposed by tuning the concentration of Ca^{2+}, Mg^{2+} and $SO4^{2-}$ ions in injection water will lead to the variation of oil recovery since those ions are the potential determining ions (PDI) which significantly contribute to the wettability alteration of carbonate rock. It is also described that during the LSWI proses, temperature plays an important role in the chemical reaction that occurs between the injection water and carbonate surface resulting in the addition of oil recovery [1,24,37,45,48]. Lastly, Al-Attar et al. [2], Al-Harrasi et al. [3], Alameri et al. [6], Hidayat et al. [23], Nasralla et al. [34], Shehata et al. [35], Tetteh et al. [40] Yousef et al. [44–46] stated that lowering the salinity of water injection until a certain value and tuning its composition will generate more oil recovery along LSWI process.

The sensitivity study of LSWI on carbonate reservoir has been discussed in several previous works. In 2014, Han & Lee conducted a study on sensitivity analysis on the combination of EOR between LSWI and Polymer Flooding. This experiment showed a large increment in oil recovery occurred when the slug size of the LSWI was increased and the highest oil yield was obtained when the viscosity of the polymer flooding was increased 2–3 times than the oil viscosity. In this study, salt concentration was analyzed to bear a less significant role in increasing oil recovery.

Al-Shalabi et al. [4] conducted a sensitivity analysis of 7 LSWI parameters using the Design of Experiment (DoE) method. It was found that the most significant parameters of LSWI in oil recovery were LSWI Slug Size, followed by Reservoir Heterogeneity, and Injected Water Salinity. The other parameters such as Kv/Kh, Sorw, and Seawater Slug Size recorded as insignificant parameters to gain the oil recovery.

Zeinijahromi et al (2015) conducted a sensitivity analysis to see the effect of the decrease in relative permeability caused by LSWI on the increase in oil recovery in the Zichebashskoe field. This study indicates that the increase in oil recovery is greatly sensitive to the decrease in water relative permeability during LSWI.

Davarpanah & Mirshekari [15] executed the sensitivity analysis of reservoir and rock properties during the LSWI process. The authors concluded that rock compressibility possess less effect on Total Field Oil Production (FOPT), Total Field Gas Production (FGPT), Field Pressure Ratio (FPR) and Field Gas Oil Ratio (FGOR). Moreover, porosity and Net to Gross reported have an important role in the generating of FOPT, FGPT, FGOR.

Recently, Egbe et al. [17] conducted a sensitivity analysis of several LSWI parameters on a carbonate reservoir using 3–6 simulation scenarios. This study recorded that higher oil recovery was obtained when injecting LSWI at the secondary stage rather than the tertiary stage. Also, he concluded that the injection rate and temperature are important in the LSWI process and must be included in the modelling process.

Machine learning has gained popularity in data science since the rapid development of computing technology. It can easily deal with the larger and complex dataset [29]. Among the variety of machine learning method, the Random Forest Algorithm is one of the most powerful methods in analyzing the data and has been implemented in many research works. It is happened due to random forest algorithm can provide high and stable predictive results, has minimal effort in tuning its parameters and can be applied both for classification and regression cases [30].

Random Forest is an advanced decision tree technique that can be used for classification or regression. It is also part of the ensemble learner family [13]). A decision tree is an easy to use method because of its clear structure. Unfortunately, the high variance makes it unstable [29]. Random forest emerges to deal with this issue. Random Forest is a process of creating many different decision trees with different sets of samples at each node and averaging the score of each decision trees as its final score to get a more accurate result [29]. Random is robust than decision tree to outliers and in unbalanced datasets, scalable and capable for handling non-linear trends in the dataset. Also, it decreases bias and overfitting in shuffling the training data using multiples trees [7]. This method has a great performance due to applying the bootstrapping technique; random forest can provide high accuracy prediction and reduce the error value, variance and prevent overfitting of the predictive model [22,30]. Unlike multivariate regression and neural network, random forest is highly interpretable. It does not require any specific data distribution and variable normalization with different range because the random forest needs not rescaled, transformed or modified [8,29]. The Random Forest Algorithm has been quite successful, cited from the many citations that indicate its practical significance in the academic or industrial application [30]. Hence, in this article, the concept of random forest is carried out to perform the sensitivity parameter of the LSWI method.

The use of random forest in doing features importance/sensitivity study in the oil and gas industry has been described in several publications. Aulia et al. [11] conducted a sensitivity analysis to see the significant parameters that affect oil recovery and water cut. The authors used the Latin Hypercube Monte Carlo (LHMC) to conduct sampling of 100 simulation runs. They also compare the One-Variable-At-A Time Perturbation (OVAT) and the Random Forest (RF) method in conducting a sensitivity study. RF calculates the Mean of Decrease of Accuracy and Mean of Decrease of Gini Index to see the significant parameter (sensitivity). The results of this study indicated that OVAT and RF have the same tendency to provide a list of parameters that most influence the response variables. Also, the changing of the number of trees on the RF can affect the sensitivity chart.

In 2017, Aulia and his co-workers conducted a sensitivity study using 10 parameters. The authors used two methods to perform sensitivity analysis, which is One-Parameter-At-a-Time (OPAT), a standard sensitivity analysis method that is often used in the upstream industry and the combination of Random Forest (RF) - Plackett-Burman (PB). Based on the result, it was concluded that RF-PB has better performance in performing sensitivity analysis compared to OPAT.

Liang & Zhao [29] conducted a EUR prediction for Unconventional Hydrocarbons in the Eagle Ford Formation. In this analysis, the authors use production/petrophysical/engineering data with 25 variables over 1069 wells in the Eagle Ford Shale Formation which will be analyzed using Multivariate Regression and Random Forest Algorithm. The author also investigates the most important parameter in estimating EUR. Based on the analysis, it found that Random Forest gives a better performance with a prediction on oil and gas EUR model of R^2 60.69% and 73.73% while the multivariate regression shows R^2 of 49%.

Liao et al. [30] conducted a prediction and parameters optimization for tight oil formation located in the Cardium Tight Oil Formation, Canada. In this analysis, the authors use 50 parameters from 1286 wells. The author also compares the performance of several Machine Learning techniques such as XGBoost, SVM, Neural Network, Random Forest, K-Mean and Gaussian Regression to determine the related parameters and their error values. It is concluded that Random Forest has the lowest error generalization rate to achieve the highest performance and its prediction score is greater than 90%.

To optimize the implementation of LSWI concerning achieve an increase in economic oil recovery, it is crucial to eliminate the uncertainties and identifying the most significant LSWI parameters to improve the recovery oil [4]. Therefore, using a random forest algorithm, in this study the author will build a predictive model which define the oil recovery as the response variable and analyze the sensitivity of LSWI parameters focusing on the ionic composition of injection and formation water such as Ca^{2+}, Mg^{2+}, SO_4^{2-}, Na^+ & Cl^-. Besides, this study also included the other LSWI parameters, are Reservoir Temperature, Injection Temperature and Injection Volume, which considered important by several published research mentioned previously.

2. Methodology

To the best of our knowledge, there is only a single reported LSWI field implementation on carbonate reservoir. Therefore, in this study, 1000 design of experiment were established using CMOST from CMG to reach the need of a dataset that will be analyzed by machine learning random forest algorithm.

1. Simulation data and design of experiment
   a. Hydrocarbon component & rock properties

The hydrocarbon component and rock properties data used in this study is referred to in the article by Yousef et al. [45] and Esene et al. [18]. The data are described in Table 1, 2 and 3. Table 4 shows the Design of Experiment of LSWI parameter.

Table 1 Fluid and rock properties [18].

Properties	Value	Unit
Saturated Pressure	740	psi
GOR	247	scf/stb
FVF	1.18	bbl/stb
API	40	
Permeability	40	md
Porosity	25	%
Reservoir Temperature	186	F
Reservoir Pressure	2515	psi

Table 2 Formation and low salinity water concentration [45].

Ions	Formation water (ppm)	Lowsal water (ppm)
Sodium (Na^+)	59,491	915
Calcium (Ca^{2+})	19,040	32.5
Magnesium (Mg^{2+})	2,439	105.5
Sulphate (SO_4)$^{2-}$	350	214.5
Chloride (Cl^-)	132,060	1610
Carbonate (CO_3)$^{2-}$	0	0
Bicarbonate (HCO_3)$^-$	354	6
Total	213,734	2883.5

Table 3 Crude oil composition [18].

Component	Mole Fraction
CO_2	0.01183
N_2	0.00161
C1	0.11541
C2	0.06006
C3	0.06476
i-C4	0.02217
n-C4	0.04755
i-C5	0.03282
n-C5	0.03703
C6	0.06514
C7	0.08420
C8	0.09894
C9	0.07838
...	...
C30+	0.06452

Table 4 Design of experiment LSWI Parameter.

Variable Name	Code/Symbol	Minimum	Maximum
Aqueous Ca Composition (ppm)	Aqu_Ca	1396.16	45375.07
Aqueous Cl Composition (ppm)	Aqu_Cl	24537.55	318854.98
Aqueous Mg Composition (ppm)	Aqu_Mg	178.05	5786.54
Aqueous Na Composition (ppm)	Aqu_Na	4909.61	159562.44
Aqueous SO_4 Composition (ppm)	Aqu_SO4	47.05	1529.06
Injection Ca Composition (ppm)	Inj_Ca	2.5	81.25
Injection Cl Composition (ppm)	Inj_Cl	123.65	4018.52
Injection Mg Composition (ppm)	Inj_Mg	8.11	263.72
Injection Na Composition (ppm)	Inj_Na	70.32	2285.41
Injection SO_4 Composition (ppm)	Inj_SO4	16.5	536.13
Volume Injection (bbl/day)	Inj_Stw	132.85	332.12
Injection Temperature (F)	Inj_Temp	139.5	232.5
Reservoir Temperature (F)	Tres	139.5	232.5

b. Reservoir model

This study is conducted using a conceptual reservoir model (See Fig. 1) with the characteristic of model can be seen in Table 5.

Table 5 Reservoir characteristic model.

Parameter	Value	Comment
Grid Number	1445	3D (17 17 5)
Pattern Area	1	Acre
Thickness (k)	50	ft
Grid size	di = 17*13	ft
	dj = 17*13	

2. Random forest hyperparameter

Similar to decision trees, the Random Forest algorithm has several hyperparameters that must be detuned to obtain an optimized prediction score. The hyperparameters are:

- Maximum trees: The maximum number of trees established during the random forest modelling process.
- Maximum depth: The maximum number of layers/branches from the root node to the deepest leaf node.
- Minimum sample leaf: The minimum number of samples required in the leaf node before splitting the node.
- Maximum features: The maximum number of features used in the splitting node process.

The following Table 6 describes the minimum and maximum value of random forest hyperparameters used in the tuning process along building the predictive model.

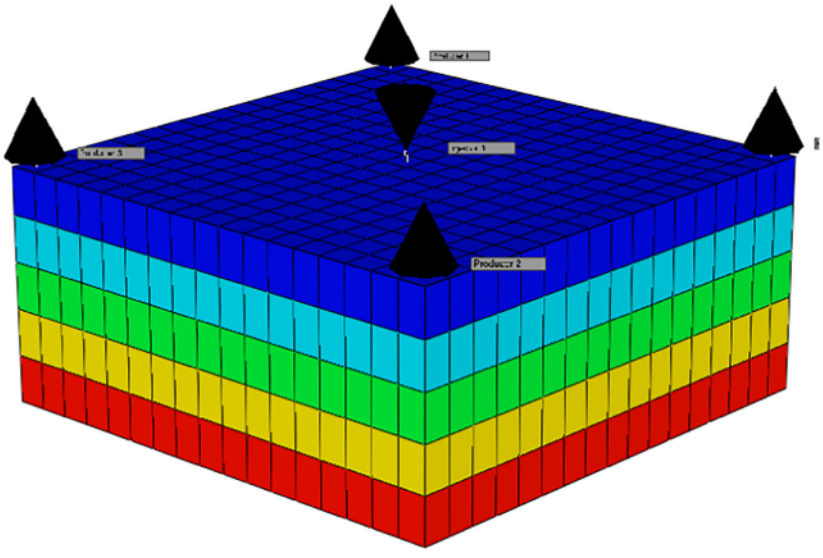

Fig. 1 Reservoir model.

Table 6 Hyperparameter of random forest algorithm

Hyper Parameter	Code/Symbol	Minimum	Maximum
Maximum Tree	'algo__n_estimators'	100	200
Maximum Depth	'algo__max_depth'	20	80
Maximum Features	'algo__max_features'	0.1	1
Minimum Sample Leaf	'algo__min_samples_leaf'	1	20

3. Result and discussion

Random Forest Supervised Machine Learning Algorithm has been widely implemented in the petroleum industry and has proven to own good accuracy and performance in predictive modelling and feature importance [7–11,29,30,33,42]. Comparison has been made with several popular machine learning algorithms such as Multivariate Linear Regression, Neural Network, Support Vector Regressor, and K-Nearest Neighbors and another ensemble method, Decision tree, alongside with Random Forest. It is intended to evaluate the performance of each algorithm in building a proxy model using the collected data. Among the algorithms used, the Random Forest has the most superior performance, as shown in Fig. 2.

Random Forest outweighs other machine learning algorithms in every parameter, bar training score from KNN. However, for KNN, the overfitting does happen as the validation and test score were under 0.6. Nevertheless, this result adds more confidence to use the Random Forest Regressor in investigating the features importance or a sensitivity study of the LSWI implementation on carbonate reservoirs.

Features importance for the Random Forest Algorithm is managed by exploring the decrease in Mean Squared Error (MSE) over 13 independent LSWI parameters. By using these independent parameters, Reservoir Temperature, Injection Temperature, Volume / Slug Injection, Injection Water Composition (Ca^{2+}, Mg^{2+}, SO_4^{2-}, Cl^-, Na^+) and Formation Water Composition (Ca^{2+}, Mg^{2+}, SO_4^{2-}, Cl^-, Na^+), and the Recovery Factor as the response parameter, 1000 Design of Experiments (DoE) based on Response Surface of Methodology were carried out using CMOST from the Computer Modeling Group (CMG) to create a dataset that will be analyzed using the machine learning method. In this study, the hyperparameters of Random Forest was also detuned to obtain the best predictive model.

In performing feature importance using Machine Learning Random Forest, first, a predictive model is built with the LSWI parameter as the input features and the Recovery Factor as the output feature. A simple Exploratory Data Analysis (EDA) is conducted by looking at the correlation between the independent variables. It is intended to ensure that there is no multicollinearity in the dataset. Multicollinearity is a condition to allow the correlation between the independent variables. In this case, the independent variables are not only correlated with the dependent variable but also correlated to each independent variables. This phenomena can lead to an increase in standard errors and can cause certain variable statistically insignificant [29]. Fig. 3 indicates that there is no multicollinearity on the dataset.

The predictive model is established by tuning the hyperparameter of the Random Forest Algorithm and splitting the dataset into 3 parts, are training data, validation data and testing data, to find the best model and prevent overfitting (I. [19,22,28]. Random Forest is an algorithm that bearing many hyperparameters [7,13]. Hence, in this study, the Randomized Search Cross-Validation technique is implemented to reduce the computation time when running the model. Randomized Search Cross-Validation is an alternative method to Grid Search Cross-Validation in performing hyperparameter optimization and suits for algorithms that have many hyperparameters such as Random Forest [28]. This method allowing us to define the number of iterations/combinations of hyperparameter that will be applied to the model. In this study, 50 iterations/combination of hyperparameter is run on the model. Moreover, 3 K-fold cross-validations and 5 scenarios of random state value are employed to analyze the consistency of

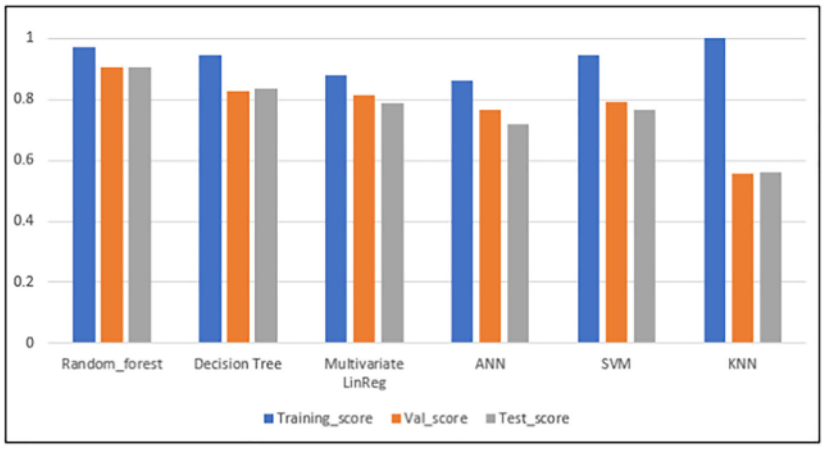

Fig. 2 Random Forest Comparison with Other Algorithms.

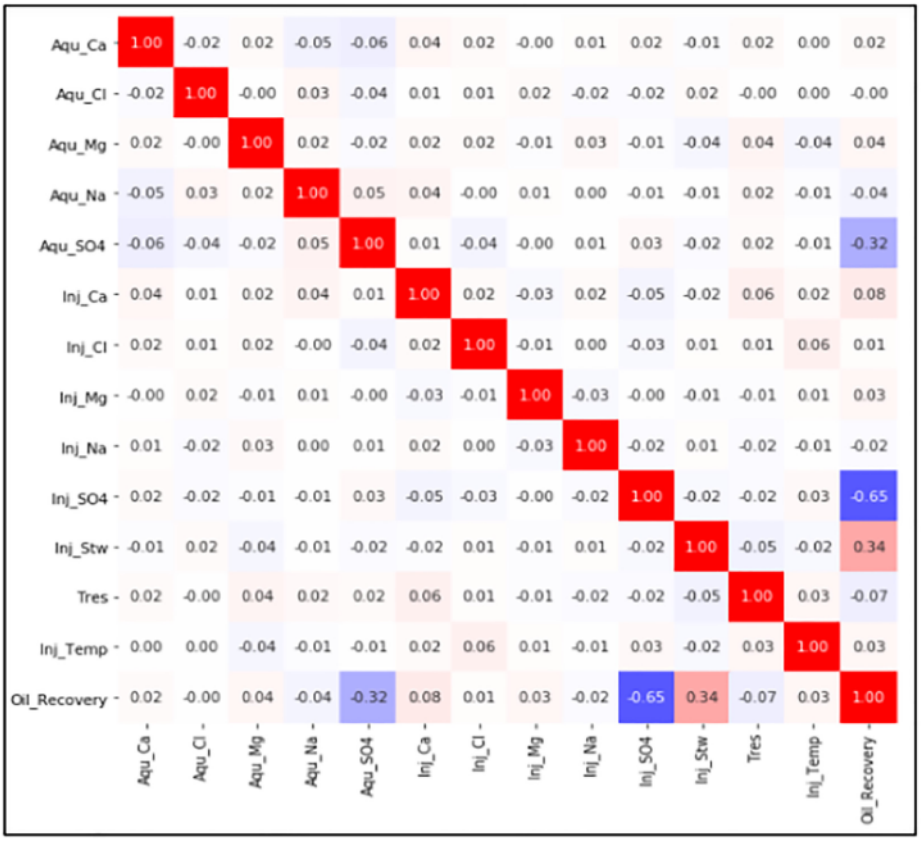

Fig. 3 Features correlation.

random forest performance in building the model. Finally, there are 150 fitting models which will be built for each random state as showing in Fig. 4.

Table 7 showed the best prediction score over 50 hyperparameters combinations. This result indicates that the random forest algorithm is successful in constructing the model due to the consistency of its performance to reach about 0.9 R^2 for all the variation of the random state value.

Fig. 5 & Fig. 6 presented the Plot Actual VS Prediction and the residual plot for evaluating the quality of the model. The R^2 in both the training data and the test data reach a score of 0.9. As indicated from those figures, the oil recovery (response variable) and loss data are symmetrically distributed near the regression line. This evaluation concluded that random forest has built a predictive model well, thus the analysis of feature importance can be confidently performed.

In the Random Forest Algorithm, Features importance is done by calculating the decrease in the Mean Squared Error (MSE) of the predictive. The more important a parameter, the greater its role in decrease the MSE [8,29]. Based on Fig. 7 & Table 8, Random Forest acknowledges the parameters of Injection SO_4^{2-} Concentration, Formation SO_4^{2-} Concen-

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Fitting 3 folds for each of 50 candidates, totalling 150 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  42 tasks       | elapsed:   41.7s
[Parallel(n_jobs=-1)]: Done 150 out of 150 | elapsed:  2.9min finished

{'algo__max_depth': 80, 'algo__max_features': 0.849875420562548, 'algo__min_sam
ples_leaf': 3, 'algo__n_estimators': 177, 'prep__numeric__poly__degree': 1, 'pr
ep__numeric__poly__interaction_only': False}
0.9690310430069371 0.9023400836964831 0.9056860027705256
```

Fig. 4 Running model using 42 random state.

Table 7 Best hyperparameter combination

No	Random State	Hyper Parameter Random Forest				Evaluation Score		
		Max_depth	Max_features	Min_samples_leaf	n_estimators	R^2	MSE	MAE
1	1	59	0.73726	2	187	0.88018	1.98363	0.71818
2	10	79	0.33474	1	147	0.93169	1.1955	0.64327
3	20	78	0.26786	3	119	0.91827	1.19444	0.68542
4	30	59	0.73726	2	187	0.93467	1.27832	0.68324
5	42	79	0.84987	3	177	0.9056	1.54809	0.71875

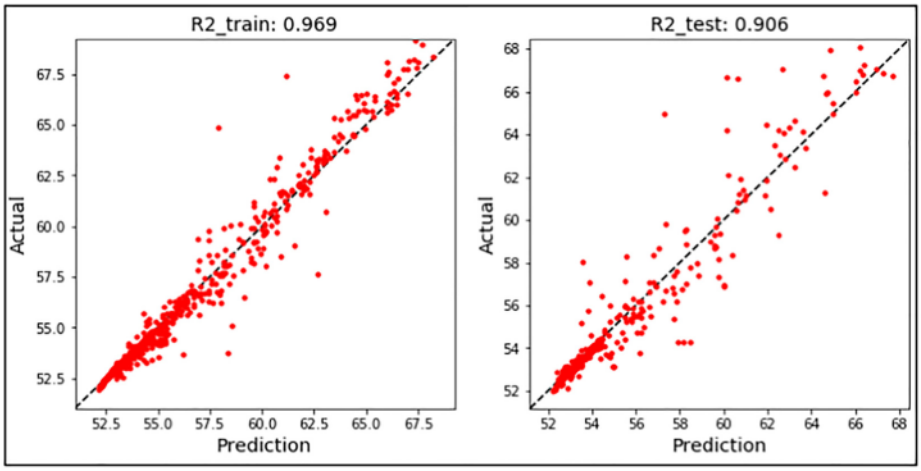

Fig. 5 Actual vs prediction plot.

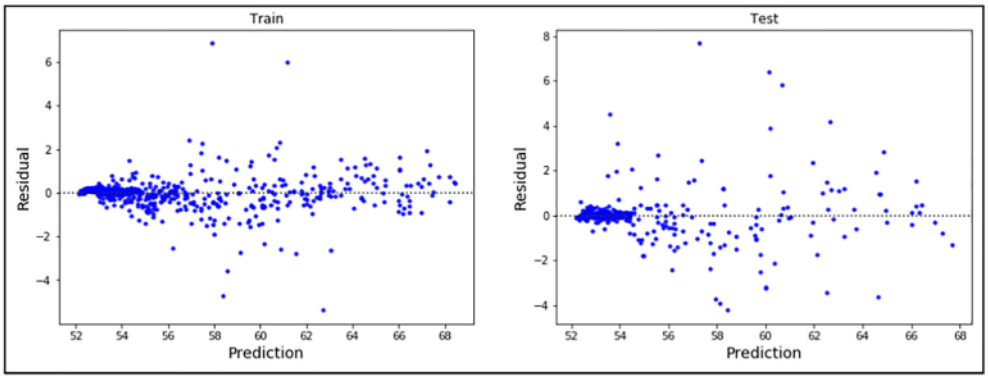

Fig. 6 Residual plot..

tration and Slug/Volume Injection, as the three most important parameters to reduce the Mean Squared Error of the model. Accordingly, these three parameters are the most significant parameter to produce oil during the LSWI process on the Carbonate Reservoir. Moreover, The other 7 parameters do not appear to have a significant role in oil recovery during the LSWI process.

The results obtained from this study are consistent with the conclusion from many published research. During the LSWI process on the carbonate reservoir, sulfate ions both in injection and formation water play an important role in oil recovery [1,2,12,16,17,20,24,37,41,48]. The injection sulfate ion is the main contributor to the wettability alteration of carbonate rock during the LSWI process. Meanwhile, the formation of sulfate ion has a significant role in the initial wetting state of the carbonate reservoir [1,17]. It was also found that volume injection is one of the most significant parameters to obtain the oil. These results are linear with several other research pub-

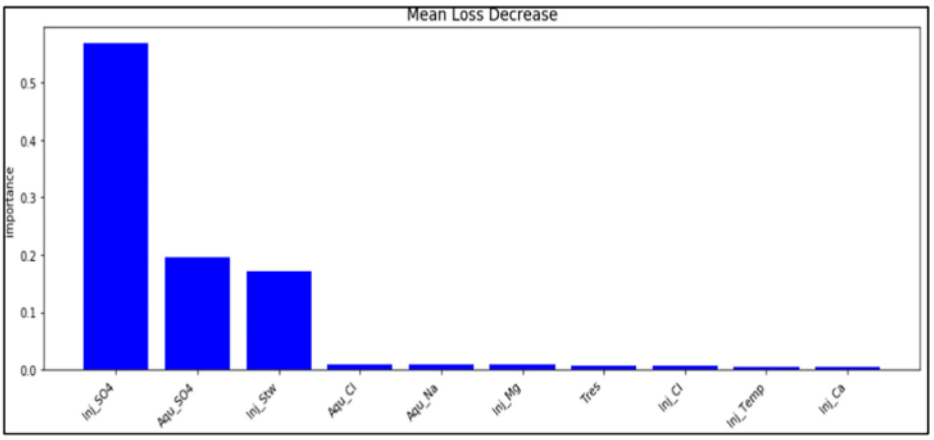

Fig. 7 Significant parameter of LSWI.

Table 8 Top 10 significant parameter LSWI.

Ranking	Features	Importance
1	Inj_SO4	0.567807
2	Aqu_SO4	0.19615
3	InjectorStw	0.171791
4	Aqu_Cl	0.009924
5	Aqu_Na	0.008429
6	Inj_Mg	0.008187
7	Tres	0.007599
8	Inj_Cl	0.006555
9	Inj_Temp	0.005575
10	Inj_Ca	0.005309

lications [4,17,21,32]. This parameter is explainable since the LSWI is an advanced technique of waterflooding where ions in water are controlled to increase oil recovery. LSWI improves both physical and chemical displacement. The physical displacement rapidly occurred since the water injection began whereas the chemical displacement began after the ions in brine reacts with the rock surface [36]. Therefore, the slug/volume injection is an important parameter in produce oil during the LSWI process.

In this study, neither injection nor reservoir temperature appears to have a significant effect in oil recovery. Both parameters only have an important value of 0.005575 & 0.007599, respectively. This result contradicts the conclusions presented by several authors in their article which they proposed that temperature is a significant parameter in the LSWI process to gain the oil [1,24,37,45,48]. A recent study from Egbe et al. [17] found that temperature have a crucial role in ion-exchange equivalent fraction Mg^{2+} and Ca^{2+}, mineral behavior and pH. They explained that the temperature did not play a significant role in increase the oil recovery where there is very little change in the oil recovery as the injection temperature changes. It happens because the oil recovery is primarily a function of the relative permeability interpolation, and no change was analyzed on it during the temperature changes.

Lastly, an attractive result found in this study is the effect of Na^+, Cl^-, Ca^{2+} and Mg^{2+} ion in oil recovery. Chandrasekhar et al. [14], Shehata et al. [35] and P. Zhang et al. [47] concluded that the concentrations of Ca^{2+}, Mg^{2+} and SO_4^{2-} are the potential determining ions (PDI) which have a major influence on changes in rock wettability and leading to increasing the oil recovery. However, it was found that the concentrations of Ca^{2+} and Mg^{2+} both in the formation of water and injection water did not have a significant effect in oil recovery during the LSWI process. Adegbite et al. [1] proposed that the Ca^{2+} and Mg^{2+} are not bearing a significant role in wettability alteration. They explained the wettability alteration that occurs in the carbonate reservoir during the LSWI process is mainly caused by the concentration of SO_4^{2-} ions. Awolayo et al. [12] also stated that both Cl^- and Na^+ are inactive ions and do not have a significant effect to generate oil recovery. Awolayo et al. [12] affirmed that the extraction of oil recovery during LSWI is a consequent of wettability alteration which is mainly contributed by the sulphate ion concentration.

4. Conclusion

This study applied a Machine Learning Algorithm based on Random Forest Regression for eliminating the insignificant parameter and evaluating the correlation between each parameter and response parameter on the LSWI process. The parameters of Injection SO_4^{2-} concentration, Formation SO_4^{2-} concentration and Volume Injection are found as the top three influenced parameters to gain the oil recovery during the LSWI process on the carbonate reservoir with each importance value is 0.567807, 0.19615, 0.171791. Whereas, the other 10 parameters observed in this study did not show any significant effect in oil recovery. The information about the significant operation parameter of the LSWI process has potential to be useful to encourage the LSWI implementation on Carbonate Reservoir.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

The authors would like to thank Universitas Islam Riau and PT. Chevron Pacific Indonesia for providing the funding of this research under the University Relationship Partner (URP) Program.

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