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Supervised Machine Learning and Multiple Regression Approaches to Predict the Successfulness of Matrix Acidizing in Hydraulic Fractured Sandstone Formation

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Abstract. The success rate of matrix acidizing in hydraulic fractured sandstone formation is less than 55%, much lower compared to the more than 91% success rate in carbonate formation. The need for alternative approaches to help the success ratio in matrix acidizing is crucial. This paper demonstrates a modeling technique to improve the success ratio of matrix acidizing in a hydraulic fractured sandstone formation. Supervised machine learning with 4 models of a neural network, logistic regression, tree, and random forest was selected to predict the successfulness of matrix acidizing in hydraulic fracturing. In parallel, multivariate analysis of principal component regression and partial least square regression approach were utilized to predict the oil gain of the job. For qualitative prediction, the results showed that the random forest was the best model to predict the successfulness of the job with the area under the curve (AUC) of 0.68 and precision of 0.73 in the training model with 70% of the data. Subsequently, the validation test with the rest of the data (30% data) gave 0.51 AUC and 61% precision. For quantitative prediction, the net oil gain was evaluated by using principal component regression (PCR) and partial least square regression (PLS-R). The PCR and PLS-R model gave a coefficient of determination (R square) of 0.22 and 0.35, respectively. The p-value of PLS-R was 0.047 (95% confidence interval) which indicates that the model is significant. The results of this work demonstrate the potential application of supervised machine learning, principal component regression, and partial least square regression to improve candidate selection of oil wells for matrix acidizing especially in hydraulic fractured wells with limited design data.

Keywords: Matrix acidizing, Hydraulic Fracturing, Sandstone, Machine learning, PCR, PLS-R

INTRODUCTION

Sandstone formation is commonly found in South Sumatra, Indonesia. In general, sandstone formation in South Sumatera or commonly known as KS field is shaly, has a very fine grain, has a thickness between 30 to 80 feet with an average of 54 feet, the permeability of 0.64 to 35 millidarcy (md) and average porosity of 20%. The

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porosity is considered high and low permeability according to the database from all petroleum-producing countries except Canada with a total of 30,122 reservoirs with average porosity ranging from 6.8% to 13% and permeability of 0.3 md to 120 md (Ehrenberg and Nadeau, 2005). Meanwhile other data from Columbia from 4,117 measurements, the porosity is higher with 13% to 25% (Ramón and Cross, 1997). The production contribution of this formation is about 20 % of the field production or the second largest after the limestone formation.

Common challenges in sandstone formation are low permeability and tight reservoir. As a consequence of those conditions, hydraulic fracturing as a tool to enhance production or stimulation becomes a key factor to produce the well. After some time, production naturally declined below the economic limit. As a result, re-fracturing is often conducted to resume oil production (Zhang and Chen, 2010). Unfortunately, the cost of hydraulic fracturing is considered high for the mature or late-life fields which are characterized by relatively low production and high operating cost. Therefore, there is a need to find an alternative option to extend production and improve field economics.

Matrix acidizing over hydraulic fractured wells is conducted in the KS field as an alternative to re-fracturing because of the lower cost and the opportunity to resume the production performance of the damaged formation. However, after a certain production time, the hydraulic fractured wells can undergo severe fines migration and promote formation damage. Although the common practice to resume a hydraulic fractured well is re-fracturing, it is worth noting that matrix acidizing implementation is also technically possible (Kalfayan, 2008). Hence, matrix acidizing can be a potential solution to encounter this case.

Fig. 1 shows the common practice of matrix acidizing for non-hydraulic fracturing wells and the common practice of re-hydraulic fracturing for the previously hydraulic fractured wells. In this study, we conducted an uncommon approach to conducting matrix acidizing in hydraulic fractured sandstone formation wells. Thus, suspected as the source of the success ratio is less than 55%.

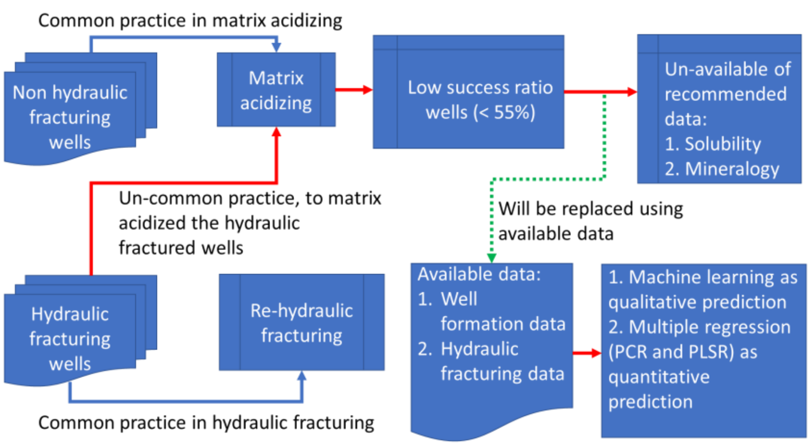

Fig. 1: The uncommon practice of matrix acidizing resulting in less than 55% success ratio and the alternative approaches to making improvements.

In general, sandstone acidizing uses a combination of HCl and HF or commonly known as mud acid. Sandstone acidizing is performed for two primary purposes: (1) to minimize perforation breakdown, and (2) to facilitate formation damage removal in the near-wellbore formation. Hydrofluoric acid (HF) is the only common acid that dissolves siliceous material which constitutes the main component in a sandstone formation. Therefore, sandstone acidizing formulation includes HF which is commonly combined with Hydrochloric acid (HCl) to attack the carbonate component and HCl soluble damage minerals in the formation. However, if the carbonate mineral content in the sandstone formation is more than 15-20%, HF should be avoided to prevent precipitation due to the excess reaction of HF and carbonate, and instead, HCl alone should be used (Kalfayan, 2008). Other alternative chemical recommendations are a chelating agent, organic acid, and organic acid-HF mixtures (Alhamad et al., 2020), (Shafiq, 2018), (Al-Harbi, 2012), (Mahmoud et al., 2011).

The success criteria for matrix acidizing are an increase of liquid and oil which exceeds the economic break-even point (BEP). The success ratio of matrix acidizing in hydraulic fractured sandstone in the KS field conducted from 2003 to 2020 is about 55%, with a total of 72 jobs. In comparison, the matrix acidizing success ratio in Baturaja formation (carbonate formation) is more than 90%. The low success ratio in sandstone matrix acidizing is a problem but at the same time offers an opportunity for scientific exploration.

The use of statistics and machine learning to predict the success rate of acidizing has been widely reported in the present literature. For instance, Tague (2000) used multivariate statistical analysis to improve formation damage remediation. Here, they reported the use of multiple regression to improve the success ratio of the acidizing process by developing selection criteria for wells. In another study, Sidaoui et al., (2018) used machine learning to predict the optimum injection rate for carbonate acidizing. The study used supervised machine learning to predict the pore volume to breakthrough (PVbt) by combining multiple variables such as fluid properties, rock properties, and operating conditions (pressure, temperature, and injection rate). The selected supervised machine learning model is a feed-forward neural network (FFNN), generate fuzzy inference system (GENFIS2), and a support vector machine (SVM). The best model was SVM which gave the highest R square of 0.88. In addition to qualitative judgment, a quantitative approach may also be used such as the use of partial least square regression (PLS-R). Liu et al. (2018) showed that PLS-R is a promising technique to predict the permeability of the formation.

In theory, the acidizing practice should be supported by the availability of solubility and mineralogy (XRD) data of rock formation (Kalfayan, 2008). Unfortunately, in reality, these data are only available in limited wells, and even worse this data is often extrapolated to the majority of candidates as the design basis. Hence, the use of machine learning and multivariate analysis is an attractive alternative to correlate common parameters in wells to the solubility and mineralogy data which later can be used to appropriately select wells with a high probability of success.

The first objective of this work was to provide a qualitative prediction on the successfulness of matrix acidizing in hydraulic fractured sandstone formation using supervised machine learning. The second was to offer a quantitative prediction of oil gain using statistical principal component regression (PCR) and partial least square regression (PLS-R). For that purpose, we have conducted data mining to process data related to well properties, acidizing parameters, and hydraulic fracturing properties. This work is expected to increase our understanding to predict the success ratio of matrix acidizing in hydraulic fractured sandstone formation, especially in the KS field in Indonesia.

METHODOLOGY

Data mining

This study was initiated by collecting data from various sources as illustrated in Fig. 2. Some portion of the data is already available in centralized digital data. However, most of the data were available in a manual folder in excel format and pdf format. These data were then picked and collected manually in a scatter location to construct a matrix acidizing data set. Matrix acidizing data were collected from jobs conducted in sandstone formations from 2013 to 2019 with a total of 72 oil producer wells. The most probable variables have been selected which include wells properties, job execution parameters, and hydraulic fracturing properties. Jobs are categorized as successful if it meets three criteria: net positive liquid gain, positive oil gain, and the oil gain is higher than the economic limit.

The data set is illustrated in Table.1 after all data were collected from the data mining process as described in Fig. 2. Approximately, 72 completed matrixes were acidizing in hydraulic fractured sandstone formation wells. The variables are formation properties, hydraulic fracturing, and acidizing. Table 1 shows the result of data mining as an input to the model which covers well properties, job parameters, and hydraulic fracturing aspects. For well properties, the selected parameters are permeability, porosity, net formation, carbonate fraction, shale fraction, reservoir pressure, current reservoir pressure, and reservoir pressure threshold. For hydraulic fracturing, features include fracturing length, fracturing width, fracturing height, fracturing volume, closure pressure, closure gradient, downhole injection pressure, current closure pressure, current closure gradient, acid volume, and gallon per foot acid. Eventually, for the job parameter, it includes the maximum injection pressure and acid pumping rate. These data were then used as the basis for machine learning and multivariate analysis to predict the success and oil gain. The orange software also uses to visualize cluster analysis as well as identification of significant features to determine the successfulness of matrix acidizing in hydraulic fractured well using the Free Viz feature.

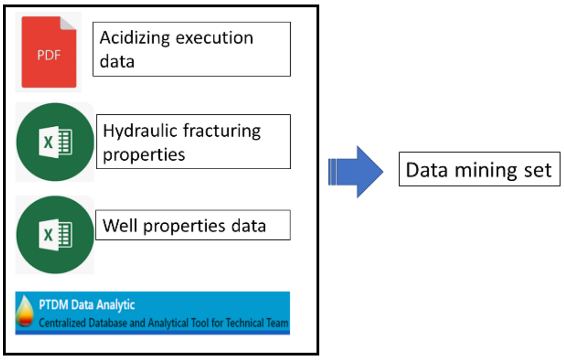

Fig. 2: Data mining process to study the success ratio of matrix acidizing in a hydraulic fractured sandstone formation.

Supervised machine learning simulation

After data mining was completed, modeling work was conducted to predict the successfulness of the matrix acidizing in hydraulic fracturing wells. All the data were set as input variables in the orange data mining software (freely available from https://orangedatamining.com/) to perform model screening. The output of this part was to provide the best model which predicts a successful or unsuccessful job.

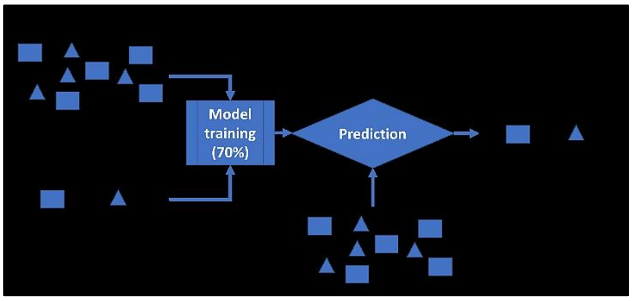

Fig. 3: Order of the data processing in the orange software.

Fig. 3 shows the diagram of data processing using orange software using supervised machine learning. The orange software version of 3.30 was utilized to screen various models such as logistic regression, neural network, tree analysis, and random forest (Uddin et al., 2019) to describe our data. In this study, 70% of the data were used to run the model and 30% of the data were used as a test. The outputs of this simulation include test accuracy for each model, confusion matrix, and prediction results.

Principal component regression using SPSS

Other than qualitative analysis, one can also propose a regression model to predict the net oil gain quantitatively. Regression is a common experiment analysis tool to describe experimental data by using a certain empirical model (Montgomery, 2013). As a result, this method may serve as a complementary criterion to evaluate the successfulness of the matrix acidizing. For this purpose, statistical modeling was conducted using SPSS IBM software. Because all variables were multicollinear, which means one independent variable was correlated with another independent variable, then the principal component regression was selected instead of multiple regression.

The first step in conducting principal component regression was to run the Kaiser-Meyer-Olkin measure of sampling adequacy, and bartlett's test. Iteration of variables selection was conducted to achieve communalities above 0.5 which means each variable accounted for the components.

Table 1. Data mining set for matrix acidizing in hydraulic fractured sandstone formation from 2013 to 2019. (k) Permeability, P (porosity), AV (acid volume), and GPF (gallon per foot).

No	Well	Success Remark	k	P	. .	AV	GPF
1	0235	Un-successful	7.3	0.2		1900	95
2	0095	Un-successful	26.9	0.27		2000	100
.							
.							
71	0244	Successful	2.15	0.17		747	40
72	0221	Successful	12.34	0.23		1244	60

The principal component analysis was then conducted to evaluate the cumulative variance explained by the principal components. The minimum target of explained variance was 60% with an Eigenvalue of more than 1. The principal component regression was then carried out. The model was then evaluated by calculating the coefficient of determination (R square value) and analysis of variance (ANOVA). Regression coefficients were also generated to provide the equation to predict the oil gain.

Partial least square regression

As a comparison to the principal component regression, this study also proposed the use of partial least square regression (PLS-R). In this study, the PLS-R was used to predict the oil gain from the matrix acidizing using variables from well properties and hydraulic fracturing. PLS-R was also selected because some of the variables are correlated, and this approach is widely used to solve the issue. ANOVA test was used to evaluate the significance of the proposed model using Minitab software.

Combining supervised machine learning and multiple regression

By combining the successfulness prediction using orange software and oil gain prediction using SPSS software, this study attempted to develop a systematic chart to predict the success of future matrix acidizing in the hydraulic fractured well. The method that was demonstrated here is expected to increase the net oil gain as well as minimize the cost of matrix acidizing in a hydraulic fractured well. Fig. 4 shows the flow process of the research which consists of data mining, successfulness criteria, input variables, supervised machine learning prediction of successfulness, and the oil gain prediction stage.

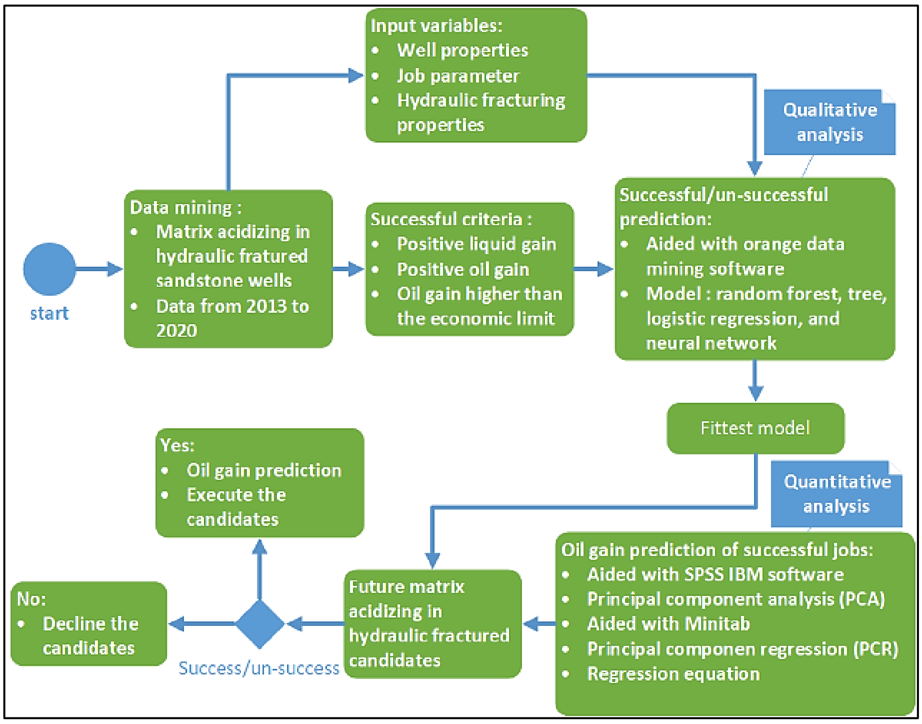

Fig. 4: Process flow diagram of the research combining machine learning (Qualitative analysis) and multiple regression (Quantitative analysis) for success/un-success oil gain prediction.

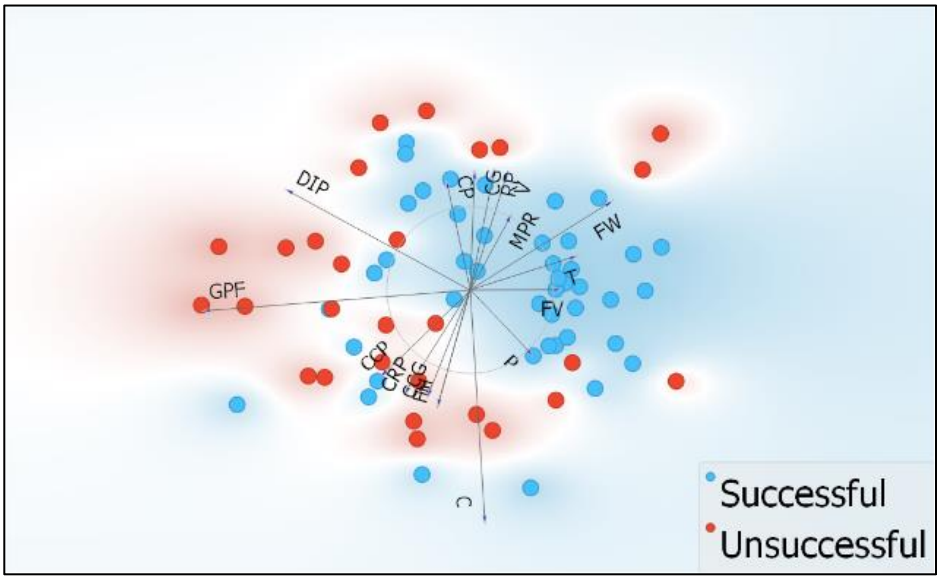

Fig. 5. Free Viz tool in orange software to visualize the variables that greatly affect the successfulness of the matrix acidizing in hydraulic fractured wells.

RESULTS AND DISCUSSION

Simulation with the Free Viz tool was carried out to analyze major variables that greatly affect the success of matrix acidizing. The results are shown in Fig. 5. The blue and red dots show successful and unsuccessful jobs, respectively. The variables are indicated by the arrow, the longer the arrow the higher the impact. The Blue area (successful job) can be separated from the red area (un-successful job) and the variables that greatly affected the success of the job are permeability (k), porosity (P), reservoir pressure (RP), closure pressure (CP), closure gradient (CG), shale fraction (V), perforation length (PL), maximum pumping rate (MPR), acid volume (AV), fracturing width (FW), fracturing length (FL), reservoir pressure threshold (T), maximum injection pressure (MIP), and fracturing volume (FV).

Successful and unsuccessful prediction using supervised machine learning

Model evaluation for matrix acidizing in hydraulic fractured wells was investigated using supervised machine learning with four models of logistic regression, neural network, tree, and random forest resulting. Table 2 presents the result from model training using 70% of the data. The values of area under the curve (AUC) for the random forest, tree, neural network, and logistic regression with of 0.68, 0.59, 0.50, and 0.51, respectively. The minimum acceptable AUC value was set to 0.5 which is the following literature (Mandrekar, 2010). A value of AUC below 0.5 is considered to deliver a failure model. Therefore, the acceptable models are random forest, tree, and logistic regression.

Table 2. Model evaluation for matrix acidizing in hydraulic fractured wells with random forest, tree, neural network, and logistic regression.

Model	*AUC*	*Precision*
Random forest	*0.68*	*0.73*
Tree	0.59	0.60
Neural network	0.50	0.56
Logistic regression	0.51	0.54

Table 3 shows the test result for the remaining 30% of data where the software did not have prior "knowledge" of the acidizing results. Logistic regression and random forest exhibited a value of AUC and precision above 0.5. Therefore, the two models can predict the successfulness of the matrix acidizing.

Table 1. The value of AUC and precision of machine learning models using 30% of remaining data of matrix acidizing.

Model	*AUC*	*Precision*
Logistic regression	0.58	0.62
Random forest	0.51	0.61
Neural network	0.47	0.51
Tree	0.50	0.51

After screening 4 models, as presented in Table. 2 and Table. 3, to predict the successfulness of matrix acidizing in a hydraulic fractured well, it appears that the best model was the random forest. Table 4 shows the confusion matrix from the random forest model validation test by comparing the actual and predicted data. It is worth noting that model validation was conducted by using 30% of the data set. It shows that the random forest model shows good performance in predicting the successfulness of the matrix acidizing job, where the desired results were shown in the diagonal elements of the table. It shows that 13 out of 21 data were correctly predicted by the model. Based on Table 4, there were only 8 out of 21 jobs that miss classified. In detail, this model misclassified the successful job as un-successful only in one well, and 7 jobs of un-successful jobs miss classified as successful. With these results, the random forest model shows a promising result as a tool to predict the success of a matrix acidizing treatment before the operation. The model is expected to increase the success ratio as well as minimize the unsuccessful operation.

Principal component regression (PCR) using SPSS

The model prediction provides quantitative analysis by predicting the oil gain results of the successful jobs using principal component regression (PCR) assisted by SPSS. Table 4 is the result of the Kaiser-Meyer-Olkin test (KMO) and bartlett's test. KMO value for the data is 0.516 and Bartlett's test results in a significant value (p-value < 0.001). KMO value is between 0 to 1, and the minimum value that the data can be analyzed using PCA is above 0.5 (Joshi and Patil, 2020), (Begdache et al., 2019).

Table 2. Confusion matrix for random forest model

		PREDICTED		
		Success-ful	Unsuccess-ful	Total
ACTUAL	Successful	**11**	1	12
	Unsuccessful	7	**2**	9
	Total	18	3	21

Table 3. Kaiser-Meyer-Olkin and Bartlett's test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	Bartlett's Test of Sphericity		
	Approx. Chi-Square	df	Sig.
0.516	642	36	0.000

Table 6 shows the communalities of the independent variables with a value of above 0.5. Communalities value is between 0 to 1, the higher the value indicating that the variable is excellence captured by the factor model (Ghozali, 2018), (Eaton et al., 2019). Eaton explained communalities value between 0.25 to 0.4 is acceptable as a cut-off, and above 0.7 is ideal. The results of communalities in this data analysis are all higher than 0.7. These variables are permeability (k), porosity (P), shale fraction (V), reservoir pressure (RP), current reservoir pressure (CRP), closure pressure (CP), closure gradient (CG), current closure pressure (CCP) and current closure gradient (CCG)

Table 4. Independent variables communalities after extraction using principal component analysis with a value higher than 0.5.

Communalities

	Initial	Extraction
k	1.000	.871
P	1.000	.854
V	1.000	.849
RP	1.000	.757
CRP	1.000	.996
CP	1.000	.957
CG	1.000	.960
CCP	1.000	.868
CCG	1.000	.990

Extraction Method: Principal Component Analysis.

The PCA results are presented in Table 7 and Fig. 6, these two analyses explain the component with an eigenvalue higher than one. The first factor can explain about 35% of the variance, the second factor explains about 30%, and the third factor was about 25%, and altogether these three components can explain more than 90% of the variance.

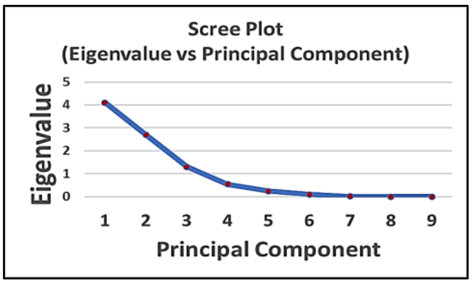

Fig. 6. Eigenvalue from 9 variables. Three variables with an Eigenvalue greater than one explain a total of about 90% of the variance.

The component matrix of the three-component is presented in Table 8. Each component can be constructed from the original variables permeability (k), porosity (P), shale fraction (V), reservoir pressure (RP),

Table 5. The total variance was explained after PCA was conducted. with three components the PCA can explain about 90% of the variance.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.103	45.585	45.585	4.103	45.585	45.585	3.142	34.908	34.908
2	2.734	30.381	75.965	2.734	30.381	75.965	2.740	30.450	65.358
3	1.266	14.065	90.030	1.266	14.065	90.030	2.221	24.672	90.030
4	.538	5.981	96.011						
5	.243	2.705	98.716						
6	.100	1.107	99.823						
7	.015	.170	99.992						
8	.001	.006	99.998						
9	.000	.002	100.000						

Extraction Method: Principal Component Analysis.

current reservoir pressure (CRP), closure pressure (CP), closure gradient (CG), current closure pressure (CCP) and current closure gradient (CCG).

Table 6. Value of three-component matrix from the original variables.

Component Matrix			
	Component		
	1	2	3
k	-.099	.806	.459
P	-.155	.754	.512
V	-.396	-.832	.007
RP	.844	-.070	-.202
CRP	.788	-.418	.448
CP	.761	.486	-.377
CG	.865	.321	-.331
CCP	.908	-.035	.205
CCG	.654	-.551	.508

Extraction Method: Principal Component Analysis.
a. 3 components extracted.

After the PCA parameter fulfilled the criteria, then regression analysis can be conducted. The resulting R square is about 0.22 as shown in table 9. At first, it seems like the resulting R square regression is low. However, for multiple regression, this value appears to be acceptable (Hatcher, 2013). According to Hatcher (2013), R square for multiple regression can be classified as 0.02 (small), 0.13 (medium), and 0.26 (large). With this reference, the principal component regression in this research can be classified as significant.

Table 7. R square value for the principal component regression

Model Summary[b]				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.466[a]	.217	.138	9.150

a. Predictors: (Constant), REGR factor score 3 for analysis 8, REGR factor score 2 for analysis 8, REGR factor score 1 for analysis 8
b. Dependent Variable: GBO

The regression coefficient of the principal component regression is represented in Table 10 of the dependent variable of Oil gain (GBO) with a constant of 20.9, coefficient 2.1 of regression factor one, -4.1 of regression factor two, and -0.52 of regression factor three. The equation then can be constructed as Oil gain (GBO) is equal to 20.9 + 2.1 regression factor one -4.1 regression factor two – 0.52 regression factor three.

Table 8. The principal component regression coefficient of the dependent variable of Oil gain (GBO) with a constant of 20.9, coefficient 2.1 of regression factor one, -4.1 of regression factor two, and -0.52 of regression factor three.

Coefficients							
	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
Model	B	Std. Error	Beta			Tolerance	VIF
(Constant)	20.902	1.569		13.31	.000		
REGR factor 1	2.102	1.593	.213	1.32	.197	1.000	1.000
REGR factor 2	-4.048	1.593	-.411	-2.54	.016	1.000	1.000
REGR factor 3	-.518	1.593	-.053	-.325	.747	1.000	1.000

a. Dependent Variable: GBO

Fig. 7 shows that the actual residual distribution is in line with the normal distribution line, and validates the normality (Joshi and Patil, 2020).

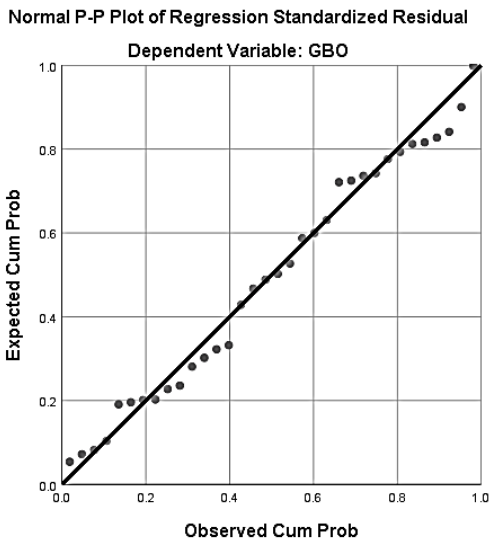

Fig. 7. The plot of the residual expected and observed. The dot value is consistently close to the line, indicating the residual is normally distributed.

Partial least square regression (PLS-R)

The ANOVA of PLS-R is shown in Table 11. An approach using Minitab to predict the oil gain of the job resulting significant value (p-value) of 0.047 using alfa of 5% (0.05) which means the regression is significant.

Table 9. Analysis of variance of partial least square regression to predict oil gain with 10 variables.

Source	DF	SS	MS	F	P
Regression	10	24684	2468	2.11	0.047
Residual Error	39	45570	1168		
Total	49	70254			

DF (degree of freedom), SS (sum of squares), MS (mean square), F (critical value), and P (significant level). The p-value is 0.047 is less than the alfa of 0.05 indicating the regression is significant.

Then, Fig. 8 illustrates the optimal R square of the regression was 0.35 which means the equation can explain about 35% of the variance and indicates other variables will explain the rest of 65%. This needs further study to evaluate another variance, which currently is not identified. According to (Kalfayan, 2008), solubility and mineralogy are the critical data to conduct matrix acidizing in sandstone formation, probably most of them are part of the 65% variables.

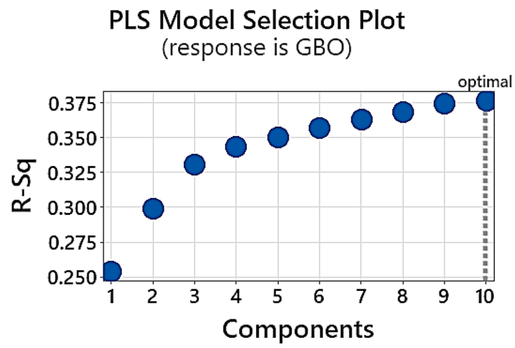

Fig. 8. Optimal R square 0.35 of partial least square using 10 principal components with the dependent variable of GBO (Oil gain).

Fig. 9 is the PLS residual normal plot with a 95% confidence level. The outer solid line is the plot of the confidence level of the individual percentiles. The residual is good if the point falls close to the center straight line. In this plot, most of the residuals fall closer to the straight line, and some of them are away and consider outliers. Moreover, zero standardized residual is more than 50% which means most of the points are fitted.

The final result for partial least square regression is the Equation (1). Table 12 is the equation coefficient to predict oil gain (GBO) using the selected variables. This equation can be utilized to predict the oil gain and screening of the future candidate. With this approach, the success ratio is expected to be increasing. The oil gain equation will be as follow:

$$GBO = -410.53 - 1.26\,k + 327.83\,P + 0.17\,h - 95.22\,C + 80.66\,V - 0.08\,RP + 0.09\,MIP + 12.97\,MPR + 0.08\,PL + 0.10\,FL + 36.19\,FW + 0.17\,FH - 0.36\,FV + 006\,CP + 381.71\,CG - 0.0\,DIP - 0.01\,AV + 0.94\,GPF \quad (1)$$

Table 10. The oil gain (GBO) regression equation coefficient for the selected variables.

	GBO	GBO standardized
Constant	-410.53	0.00
k	-1.26	-0.15
P	327.83	0.23
h	0.17	0.06
C	-95.22	-0.08
V	80.66	0.16
RP	-0.08	-0.51
MIP	0.09	0.33
MPR	12.97	0.41
PL	0.80	0.12
FL	0.10	0.23
FW	36.19	0.18
FH	0.17	0.06
FV	-0.36	-0.21
CP	0.06	0.36
CG	381.71	0.56
DIP	-0.05	-0.35
AV	-0.01	-0.07
GPF	0.94	0.20

Predictors: permeability (k), porosity (P), net pay (h), carbonate fraction (C), shale fraction (V), reservoir pressure (RP), maximum injection pressure (MIP), maximum pumping rate (MPR), perforation length (PL), Fracturing length (FL), Fracturing width (FW), Fracturing height (FH), Fracturing volume (FV), closure pressure (CP), closure gradient (CG), downhole injection pressure (DIP), acid volume (AV).

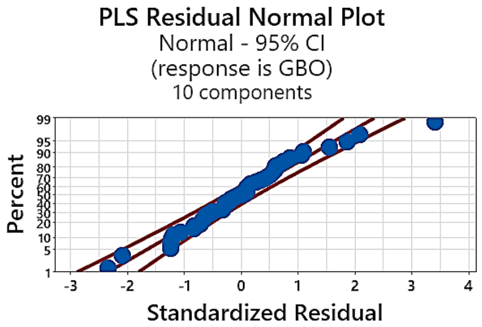

Fig. 9. Partial least square (PLS) residual normal plot. The straight line in the middle is the fitted line. If the residual is close to the straight line this is a good fit. Outer solid lines are confidence intervals for the individual percentiles.

Combination of qualitative and quantitative approach

The success of the job is greatly affected by the variables in Table 12. The approach of supervised machine learning can be utilized to predict the successfulness of the matrix acidizing in hydraulic fracturing wells as a qualitative analysis. Random forest is the best model with an area under the curve (AUC) of 0.68, and a precision of 0.61 in the data test.

To validate the model, the new data from the latest jobs were introduced to the model and resulting in 67% accuracy. Referring to the minimum validity requirement of 60%, the validity value is good.

Principal component regression is greatly supporting the quantitative analysis by predicting the oil gain from the successful matrix acidizing in hydraulic fracturing jobs. Statistical analysis can be accepted from KMO of 0.516 and significant bartlett's test with a p-value below 0.001. Principal component analysis results in 3 components that can explain more than 90% variance from 9 original variables.

The R square of the principal component regression is about 0.22 and is categorized as large from the reference. The resulting equation of Oil gain (GBO) is equal to 20.9 + 2.1 regression factor one -4.1 regression factor two – 0.52 regression factor three.

As a comparison partial least square regression (PLS-R) resulting R square of 0.35 with a p-value (significant value) of 0.047 and alfa 5% (0.05) indicate that the regressions were significant.

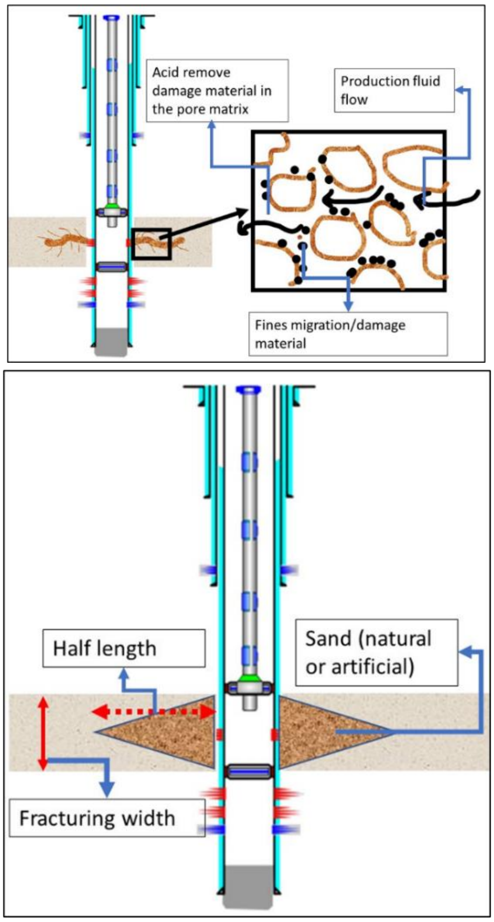

Fig. 10. Lower: Hydraulic fracturing. Upper: Matrix acidizing.

In general regression, this value is considerably low. Otherwise, in multiple regression, the R square for multiple regression are 0.02 (small), 0.13 (medium), and 0.26 (large) (Hatcher, 2013). With this reference, the regression in this research is categorized as a large effect (significant). This explanation is also supported by Montgomery (2013), which stated that the data which are not prepared for experiments will most likely produce a lower R square. These results are in line with this research data type.

Based on all models' predictions the physical phenomenon of matrix acidizing in hydraulic fractured sandstone formation can be explained from the diagram. Fig. 9 shows the illustration of the matrix acidizing and hydraulic fracturing. The upper figure is hydraulic fracturing, and the lower figure is matrix acidizing. Some variables still cannot be identified that probably impacting to the matrix acidizing performance. Future research should examine the remaining variables which highly suspected will be considered to improve the prediction accuracy.

These results imply the opportunity for supervised machine learning, principal component regression, and partial least square regression to improve the candidate selection for matrix acidizing in hydraulic fractured wells with limited design data.

CONCLUSIONS

The use of machine learning and multiple regression has been demonstrated to predict the successfulness and net oil gain in matrix acidizing of hydraulic fractured sandstone wells. Supervised machine learning with 4 models of the neural network, logistic regression, tree, and random forest has been screened to predict the successfulness of matrix acidizing in hydraulic fracturing. The results showed that logistic regression and random forest model exhibited a value of AUC and precision above 0.5. Therefore, the two models can predict the successfulness of the matrix acidizing.

In addition, for the quantitative prediction of oil net gain, the principal component regression gave an R square of

0.22. In addition, partial least square models gave an R square of 0.35 with a p-value (significant value) of 0.047 and an alfa of 5% (0.05).

The present work is expected to show an alternative method to predict the success rate of matrix acidizing in hydraulic fractured wells. The current approach overcomes the limited availability of solubility and mineralogy data in the field. The current methodology is expected to increase the success ratio for the future acidizing job by eliminating the non-suitable candidates.

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NOMENCLATURE

AUC	:	The area under the curve
PCR	:	Principal component regression
$\mathrm{PLS-R}$	:	Partial least square regression
R square	:	Coefficient of determination
PVbt	:	Pore volume to breakthrough
XRD	:	X-Ray diffraction
k	:	Permeability [milli Darcy]
P	:	Porosity [%]
RP	:	Reservoir pressure [psig]
CP	:	Closure pressure [psig]
CG	:	Closure gradient [psi/ft]
V	:	Shale fraction [%]
PL	:	Perforation length [m]
MPR	:	Maximum pumping rate [gpm]
AV	:	Acid volume [bbl]
FW	:	Fracturing width [inch]
FL	:	Fracturing length [ft]
T	:	Reservoir pressure threshold [psig]
MIP	:	Maximum injection pressure [psig]
FV	:	Fracturing volume [ft3]
KMO	:	Kaiser-Meyer-Olkin test
PCA	:	Principal component analysis
CCP	:	Current closure pressure [psig]
CCG	:	Current closure gradient [psi/ft]
GBO	:	Oil gain [bopd]
df	:	Degree of freedom
SS	:	Sum of square
MS	:	Mean square
F	:	Critical value
p	:	Significant level
h	:	Net pay [ft]
C	:	Carbonate fraction [%]
DIP	:	Downhole injection pressure [psig]

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Appendix A

Raw data of matrix acidizing in hydraulic fractured sandstone wells

Well Name	Successful/Unsuccessful	k	P	h	C	V	RP	CRP	T	MIP	MPR	APR	PL	FL	FW	FH	FV	CP	CG	DIP	CCP	CCG	AV	GPF	GBL	GBO
1	Unsuccessful	7.276	0.2	55.5	0.12	0.19	1203	1130	450	600	1.4	1	32	184	0.25	55.5	30	1831	0.67	1573	1792	0.66	1900	95	57	-4
2	Unsuccessful	26.874	0.271	6.5	0.12	0.185	570	557	450	800	3.1	2.5	10	0	0	6.5	0	1498	0.55	1775	1491	0.55	2000	100	-11	-7
3	Successful	1.353	0.19	43.5	0.15	0.473	886	886	650	800	3.9	2.5	20	486.38	0.3	43.5	75	1322	0.58	1583	1470	0.64	2200	110	71	48
4	Unsuccessful	6.644	0.203	112.5	0.14	0.306	522	529	450	800	9	9	20	435	0.13	112.5	76	1462	0.54	1765	1466	0.54	2000	100	11	2
5	Successful	9.005	0.213	72.5	0.16	0.233	811	861	450	800	2.4	1.6	11	189	0.06	72.5	10	1629	0.59	1779	1656	0.60	3024	100	139	20
6	Unsuccessful	2.511	0.221	75	0.13	0.343	421	622	650	700	2	1.8	20	263	0.21	75	49	1046	0.44	1517	1364	0.58	1932	120	0	-8
7	Successful	6.555	0.205	49	0.09	0.308	980	914	450	800	3.6	2	20	336	0.25	49	49	1686	0.63	1747	1652	0.62	882	44	182	160
8	Successful	7.543	0.209	66	0.07	0.246	439	508	450	594	4.5	2	22	206	0.217	66	35	1378	0.53	1125	1414	0.54	1176	40	38	37
9	Unsuccessful	5.714	0.192	84	0.08	0.252	969	885	450	749	1.1	0.7	40	215	0.2	84	43	1675	0.63	1792	1630	0.61	2280	110	18	3
10	Unsuccessful	12.003	0.214	88.38	0.10	0.197	990	947	450	492	5	2.6	30	200	0.2	88.38	42	1695	0.63	1501	1672	0.62	4024	134	-76	2
11	Unsuccessful	2.511	0.221	75	0.13	0.343	421	622	650	594	3.7	2.5	20	263	0.21	75	49	1046	0.44	1617	1364	0.58	941	47	-1	-3
12	Successful	23.04	0.259	53	0.06	0.231	538	469	450	607	1.8	1.6	32	552	0.061	53	21	1460	0.54	1755	1423	0.53	1621	55	164	11
13	Unsuccessful	7.276	0.2	55.5	0.12	0.19	1093	1130	450	551	1.6	1.3	32	184	0.25	55.5	30	1773	0.65	1773	1792	0.66	1433	40	-44	-5
14	Unsuccessful	11.117	0.221	44.5	0.07	0.285	1003	927	450	525	3.2	2.5	16	203	0.37	44.5	40	1706	0.64	1754	1665	0.62	782	60	-123	-2
15	Unsuccessful	9.005	0.213	72.5	0.16	0.233	808	861	450	654	2.9	2.2	89	189	0.06	72.5	10	1628	0.59	1779	1656	0.60	1303	60	32	-5
16	Unsuccessful	54.153	0.289	83.5	0.09	0.24	308	342	450	749	4	4	20	122	0.412	83.5	50	1310	0.50	927	1328	0.51	1303	60	32	2
17	Successful	7.276	0.2	55.5	0.12	0.19	1093	1130	450	526	1.5	1.2	32	184	0.25	55.5	30	1773	0.65	1773	1792	0.66	1433	40	88	19
18	Successful	12.77	0.234	59	0.07	0.319	727	620	450	492	5	5	16	200	0.2	59	28	1556	0.58	1050	1499	0.56	782	40	120	90
19	Unsuccessful	5.4	0.174	79.6	0.08	0.213	882	828	450	578	2.9	2.1	20	343	0.061	79.6	20	1648	0.61	1761	1620	0.60	912	40	14	2
20	Unsuccessful	9.119	0.224	34.5	0.05	0.382	893	901	450	525	4	2.7	14	142	0.27	34.5	16	1675	0.61	1781	1679	0.61	652	40	548	-34
21	Successful	10.838	0.216	37	0.12	0.244	387	428	450	800	2.1	1.8	14	208.88	0.83	37	76	1382	0.51	1757	1404	0.52	912	60	20	32
22	Successful	8.585	0.217	55	0.05	0.24	887	681	450	480	3.9	3.9	24	145.4	0.284	55	27	1684	0.61	1474	1575	0.57	1563	60	90	74
23	Successful	7.543	0.209	66	0.07	0.246	391	508	450	594	6	5	22	206	0.217	66	35	1352	0.52	975	1414	0.54	912	40	150	145
24	Successful	63.499	0.27	65.5	0.08	0.185	424	510	450	607	4.5	4.5	36	210	0.2	65.5	33	1382	0.52	937	1428	0.54	2344	60	72	63
25	Successful	22.954	0.261	68.93	0.10	0.004	486	870	450	300	4	4	40	234	0.26	68.93	50	1410	0.54	1232	1613	0.61	1303	60	64	60
26	Successful	3.645	0.158	72	0.08	0.226	1104	1230	450	800	1	1	15	152	0.6	72	78	1783	0.65	1777	1849	0.68	652	40	20	15
27	Successful	2.234	0.169	54.08	0.12	0.328	856	708	450	800	4	3.3	24	200	0.2	54.08	26	1666	0.60	1792	1588	0.57	1042	40	38	13
28	Unsuccessful	56.027	0.295	76.5	0.06	0.218	780	1230	450	800	6	6	30	200	0.25	76.5	45	1576	0.59	1743	1814	0.68	1303	40	0	-11
29	Unsuccessful	1.824	0.187	52	0.18	0.41	848	848	650	800	2	2	18	262	0.25	52	40	1300	0.57	1587	1454	0.63	912	40	-4	-12
30	Successful	0.609	0.156	48	0.18	0.442	743	743	650	800	3.8	3	20	190	0.47	48	51	1251	0.53	1612	1423	0.60	912	40	16	13
31	Successful	2.511	0.221	75	0.13	0.343	622	622	650	800	3.3	2.8	20	263	0.21	75	49	1176	0.50	1617	1364	0.58	1303	60	10	9
32	Successful	1.926	0.206	63.5	0.11	0.342	835	835	650	800	3.4	3	20	368	0.25	63.5	69	1313	0.56	1615	1475	0.63	912	40	72	26

33	Successful	63.499	0.27	65.5	0.08	0.185	403	510	450	800	5.5	2	36	210	0.2	65.5	33	1371	0.52	1737	1428	0.54	1493	40	128	27
34	Successful	1.618	0.198	43.5	0.14	0.461	311	810	650	800	3.5	1.5	23	426	0.22	43.5	48	966	0.41	1605	1452	0.62	871	40	13	12
35	Successful	6.479	0.279	67	0.13	0.218	683	702	650	800	3.5	2	29	327	0.3	67	78	1219	0.51	1621	1411	0.59	871	40	9	6
36	Successful	14.192	0.231	47	0.10	0.301	712	918	450	800	2.7	1.8	18	280	0.44	47	69	1538	0.58	1741	1647	0.62	747	40	212	24
37	Successful	26.874	0.271	6.5	0.12	0.185	839	557	450	800	2.4	1.5	10	0	0	6.5	69	1640	0.60	1775	1491	0.55	498	40	20	20
38	Successful	1.825	0.204	50.5	0.11	0.346	802	802	650	800	1.5	0.8	19	376	0.2	50.5	45	1298	0.55	1623	1466	0.62	871	40	20	19
39	Successful	10.838	0.216	37	0.12	0.244	415	428	450	800	1.8	1.5	14	208.88	0.83	37	76	1397	0.52	1757	1404	0.52	373	40	34	29
40	Unsuccessful	6.678	0.211	20	0.08	0.342	359	376	450	800	1.6	0.9	20	141.23	0.24363	20	8	1351	0.51	1741	1360	0.51	622	40	0	0
41	Successful	1.075	0.179	31	0.15	0.446	487	784	650	800	4.1	3.5	20	221	0.127	31	10	1063	0.46	1583	1416	0.62	995	40	12	11
42	Successful	2.221	0.215	80	0.14	0.369	844	844	650	551	2	2	36	187	0.25	80	44	1291	0.57	1583	1442	0.63	871	40	20	20
43	Unsuccessful	10.165	0.221	76	0.09	0.248	816	447	450	400	2.5	2	20	216	0.8	76	156	1623	0.60	1370	1427	0.52	871	40	52	-2
44	Successful	1.543	0.195	60	0.07	0.46	488	935	650	800	4.4	2.1	20	308	0.2	60	44	1063	0.47	1582	1494	0.65	871	40	8	8
45	Successful	9.005	0.213	72.5	0.16	0.233	726	861	450	800	2.1	1.7	89	189	0.06	72.5	10	1584	0.58	1779	1656	0.60	1244	40	190	117
46	Unsuccessful	5.714	0.192	84	0.08	0.252	674	885	450	800	1.2	0.5	40	215	0.2	84	43	1519	0.57	1742	1630	0.61	871	40	-8	-8
47	Unsuccessful	6.842	0.206	75.5	0.08	0.266	414	687	450	800	2.5	2.1	17	0	0	75.5	43	1373	0.52	1734	1518	0.58	747	40	10	3
48	Successful	54.153	0.289	83.5	0.09	0.24	756	342	450	250	2	1.4	20	122	0.412	83.5	50	1547	0.59	1177	1328	0.51	871	40	24	23
49	Unsuccessful	0.419	0.125	20.04	0.08	0.201	460	361	450	900	0.3	0.3	15	120	0.37	20.04	11	1398	0.53	1835	1346	0.51	995	60	0	0
50	Successful	1.926	0.206	63.5	0.11	0.342	835	835	650	300	2	1.7	20	368	0.25	63.5	69	1313	0.56	1115	1475	0.63	1244	60	64	28
51	Successful	9.119	0.224	34.5	0.05	0.382	843	901	450	800	2.4	1.5	14	142	0.27	34.5	16	1649	0.60	1781	1679	0.61	622	40	294	82
52	Unsuccessful	16.75	0.237	50	0.07	0.258	1230	1230	450	800	0.5	0.5	12	221	0.127	50	17	1852	0.67	1780	1852	0.67	747	60	0	0
53	Unsuccessful	0.684	0.16	67	0.18	0.397	790	981	650	800	1.7	1.5	15	423	0.2	67	67	1283	0.54	1614	1551	0.66	995	60	0	0
54	Successful	7.276	0.2	55.5	0.12	0.19	931	1130	450	800	2.5	2.5	32	184	0.25	55.5	30	1687	0.62	1773	1792	0.66	1369	40	30	10
55	Successful	5.25	0.197	58.53	0.15	0.312	738	738	450	800	2	2	30	133.8	0.436	58.53	41	1586	0.58	1775	1586	0.58	1244	40	200	17
56	Successful	2.145	0.171	48.76	0.09	0.345	592	515	450	525	2	1.5	18	228.4	0.252	48.76	33	1494	0.55	960	1453	0.54	747	40	109	54
57	Successful	3.46	0.18	57	0.06	0.28	316	625	450	655	3.1	2.6	21	186	0.68	57	86	1321	0.50	934	1485	0.56	747	40	24	15
58	Unsuccessful	11.32	0.205	48.62	0.14	0.239	459	576	450	800	0.7	0.7	16	210	0.33	48.62	40	1409	0.53	1746	1471	0.55	995	60	-20	-21
59	Unsuccessful	3.008	0.18	55.5	0.10	0.325	951	974	450	800	1.2	0.8	20	308	0.25	55.5	51	1689	0.62	1765	1701	0.63	871	40	0	0
60	Successful	5.4	0.174	79.6	0.08	0.213	931	828	450	600	3.9	1	20	343	0.061	79.6	20	1674	0.62	1561	1620	0.60	871	40	52	34
61	Unsuccessful	9.696	0.204	41.58	0.09	0.284	591	435	450	800	4.1	0.6	12	206	0.17	41.58	17	1496	0.55	1763	1414	0.52	498	40	-4	-2
62	Unsuccessful	5.379	0.203	54.92	0.06	0.238	584	1198	450	580	3	2	30	219	0.3	54.92	43	1471	0.55	941	1796	0.68	1244	40	-58	-12
63	Successful	12.77	0.234	59	0.07	0.319	583	620	450	800	3.4	2.1	16	200	0.2	59	28	1479	0.55	1750	1499	0.56	747	40	120	113
64	Unsuccessful	0.965	0.173	41	0.10	0.437	749	604	650	800	3.2	2.7	20	356	0.42	41	73	1236	0.54	1588	1325	0.58	871	40	-5	1
65	Successful	1.926	0.206	63.5	0.11	0.342	835	835	650	527	3.2	2.7	20	368	0.25	63.5	69	1313	0.56	1588	1475	0.63	871	40	41	25
66	Successful	63.499	0.27	65.5	0.08	0.185	364	510	450	800	0.3	0.1	36	210	0.2	65.5	33	1350	0.51	1737	1428	0.54	1493	40	32	24
67	Successful	56.027	0.295	76.5	0.06	0.218	670	1230	450	562	3	2	30	200	0.25	76.5	45	1518	0.57	953	1814	0.68	1244	40	19	17
68	Unsuccessful	8.926	0.216	58.74	0.13	0.281	484	1019	450	700	3.3	3.3	14	209	0.39	58.74	57	1441	0.53	1664	1724	0.64	622	40	-34	5

69	Successful	10.142	0.221	60	0.08	0.276	568	544	450	578	2	1.5	14	152	0.78	60	84	1524	0.55	1002	1512	0.54	622	40	136	18
70	Successful	15.479	0.213	70	0.08	0.225	584	1084	450	800	2.5	1	24	118	0.34	70	33	1488	0.55	1758	1753	0.65	995	40	147	22
71	Successful	2.145	0.171	48.76	0.09	0.345	424	515	450	525	2	2	18	228.4	0.252	48.76	33	1405	0.52	960	1453	0.54	747	40	52	34
72	Successful	12.335	0.232	51.82	0.09	0.243	754	830	450	600	2.2	1.5	20	218	0.69	51.82	93	1599	0.58	1579	1639	0.60	1244	60	712	22

New data from the latest jobs for validity check

Well Name	Successful/Unsuccessful	k (mD)	Porosity (Fraction)	h (ft)	Carbonate (Fraction)	Vshale	Resistivity (ohmm)	Reservoir Pressure (psi)	Max Injection Pressure (psi)	Max Pumping Rate (bpm)	Acid Pumping Rate (bpm)	Perforation Length, ft	Frac Length, ft	Frac Width, inch	Frac Height, ft	Frac Volume, bbl	Closure Pressure, Psig	Closure Gradient, Psig/ft	Downhole Injection Pressure, Psig	Current Closure Pressure, Psig	Current Closure Gradient, Psig/ft	Acid Volume (gals)	GPF	Gain BFPD	Gain BOPD
1	Unsuccessful	10.08	0.2	49	0.12	0.19	0.7	1077	570	5.5	2.3	20	145.2	0.151	81.2	25.2	1518	0.54	1974	1518	0.54	1050	53	106	1
2	Successful	7.543	0.209	66	0.07	0.246	6.2	391	594	2	2	22	206	0.217	66	35	1352	0.52	975	1414	0.54	756	34	328	239
3	Successful	5.714	0.192	84	0.08	0.252	4.8	674	800	3.9	0.2	40	215	0.2	84	43	1519	0.57	1742	1630	0.61	882	22	256	38