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Improving EOR Selection Efficiency with Novel EOR Screening Software: Applied Machine Learning

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Abstract
With the decreasing rate of production, the application of Enhanced Oil Recovery (EOR) technology is one solution to increase the recovery of oil production from reservoirs. EOR is a method to increase production by influencing the interaction between fluids and reservoir rocks. Before an EOR method is implemented, it is necessary to conduct EOR screening so that the EOR method is most suitable for field conditions and the increase in oil production is achieved optimally. Conventionally, EOR screening methods are done manually matching field parameters with criteria sourced from Taber et al (1997) and from Al-Adasani et al (2010). This method has several drawbacks including taking a long time, high subjectivity, and qualitative. As a result, screening results using this method have poor accuracy, low effectiveness, and have high uncertainty. In this study, we proposed quantitative methods for EOR screening based on automation systems in software built with Machine Learning algorithms. This screening method is based on a static and probabilistic evaluation of the most suitable combination of 8 parameters of oil and reservoir characteristics and tested on 5 different fields based on Taber et al (1997) and Al-Adasani & Bai (2010) criteria. Based on the test results, the order of conformity rating of EOR method is obtained along with the evaluation of the score. Furthermore, a comparative analysis is conducted with the results of EOR screening manually and with the results of screening using other commercial software. The results of this study show that the proposed method can produce better output because the process is efficient in terms of computational time, more reliable results, and quantitative. This method is expected to be one of the solutions for the acceleration of the EOR program in support of the target of increasing national oil production.
Keywords: Enhanced Oil Recovery, Machine Learning, Screening Technology, Software

Introduction

Hydrocarbon fields after a long-time production is going to natural decline due to the reduced energy to remove fluids from the well. The reduced propulsion force is usually overcome by installing a pump or gas lift in a natural well. However, over time, artificial lift well will gradually find it difficult to flow due to the limited drainage area. To increase the field drainage area and driving force, there are developed a few techniques that are called Enhanced Oil Recovery (EOR) or now better known as Improved Oil Recovery (IOR). But how to determine the appropriate EOR method (EOR Screening) for existing oil fields?

EOR screening is a technique to choose the right EOR method that can be used in a particular reservoir. This screening process is strongly influenced by the method of assessing the level of compatibility between the reservoir properties and the EOR method. There have been many studies and publications that discuss methods to perform statistical EOR Screening or with an artificial intelligence approach. EOR screening was initially carried out using a statistical approach but over time several other approaches have been taken such as cluster and composite methods, artificial intelligence (AI) methods and machine learning (ML) methods. Taber et al (1983) developed a technical guidance to determine the EOR method by collecting data from successful EOR projects worldwide and dividing them into two parts, there are oil properties and reservoir characteristics. The result of this study is that Taber et al. presented the technical selection criteria in the form of tables and graphs accompanied by the basis of the lifting mechanism and the limitations of each method. Al-Adasani et al (2010) updated the screening criteria for the selection of the EOR method by adding the latest EOR project data. This study adds data from the results of the EOR survey from 1998 to 2010 into the screening criteria that have been made by Taber (1997). In addition to updating the screening criteria, this study also investigates the distribution of EOR projects with reservoir properties. There is still a lot of literature that has discussed how to determine the EOR method that is suitable for a field. However, there are several gaps including: i) most of them are still manual, ii) high subjectivity, and iii) one method/technology is limited to one field or only one type of EOR method. This paper tries to fill the gap by using PertaEOR software. PertaEOR is an EOR software made by Pertamina Upstream Research & Technology Innovation (URTI) which can perform EOR screening based on machine learning and automated statistical algorithms. It is hoped that the screening results will be better, more accurate, and quantitative so the EOR methods can be compared.

Data and Method

PertaEOR was tested on 5 fields in Indonesia. The five fields are named after fields A, B, C, D, and E. The naming is to maintain data confidentiality. Field A operates in South Sumatra, Field B&E in East Java, and Fields C&D in Jambi.

Oil & Reservoir Properties

Oil and reservoir characteristics include 9 parameters including: Oil gravity, viscosity, porosity, oil saturation, formation type, permeability, net thickness, depth, and temperature. Data from 5 different real fields have been provided as in table 1.

EOR Screening

It is a process of selecting a suitable EOR method based on oil and reservoir data in a field. There are 3 types of ways / techniques are carried out including:

Manual Screening

Manual screening carried out by using guidelines from Al-Adasani & Bai (2010) and Taber et al (1997) in table 2. Oil & reservoir properties data of a field will be matched with data from tables 2 and 3. Al-Adasani & Bai (2010) and Taber et al (1997) grouped oil & reservoir properties into an EOR Method based on success stories of field implementations that have been carried out previously around the world.

Determination of the EOR method using reference data Taber et al. (1997) seen from the suitability of the oil properties and reservoir characteristics in the field, it includes 9 (nine) parameters as follows:
a. Oil API Gravity
b. Oil viscosity
c. Oil Composition
d. Reservoir oil saturation
e. Reservoir formation type
f. Reservoir net thickness
g. Average permeability
h. Reservoir depth
i. Reservoir temperature

Match level is depicted in cell colors, which are green (if the value is within the range and supports the related EOR method), yellow (if the value is slightly out of range and there is still a chance for the related EOR method), and red (if the value is outside the range).

Determination of the EOR method using reference data Al-Adasani & Bai (2010) saw the suitability of the oil properties data and reservoir characteristics in the field covering 9 (nine) parameters as follows:
a. Oil API Gravity
b. Oil viscosity
c. Oil Composition
d. Reservoir porosity
e. Reservoir oil saturation
f. Reservoir formation type
g. Average permeability
h. Reservoir depth
i. Reservoir temperature

Same with Taber et al. (1997) the match level is depicted in green (if the value is within the range and supports the related EOR method), yellow (if the value is slightly out of range and there is still a chance for the related EOR method), and red (if the value is slightly out of range.

PertaEOR

It is PERTAMINA's software that has an EOR screening module. Using machine learning with scoring and weighting based on statistical and technical algorithms. Statistical algorithms are algorithms with purely statistical data considerations. While the engineering algorithm includes engineering sense. In addition, there is also a penalty algorithm if the input data is too far from the range of criteria data that is suitable for an EOR method. The combination of all these algorithms will be used to determine the suitability rating of the input field data.

The determination of the EOR method using PertaEOR Software was based on the match of 9 (nine) oil properties and reservoir characteristics of the field to the database which included the reference of Taber et al. (1997), Al-Adasani & Bai (2010) and Oil & Gas Journal (2020). For a target reservoir, the EOR method that has the highest probability value will be selected and ranked as the best EOR method for the target reservoir. The nine parameters analyzed are as follows:
a. Oil API Gravity
b. Oil viscosity
c. Oil Composition
d. Reservoir porosity
e. Reservoir oil saturation
f. Reservoir formation type
g. Average permeability
h. Reservoir depth
i. Reservoir temperature

Other EOR Screening Software

As a reference for commercial software, EORGui from Petroleum Solutions is used. The determination of the EOR method using the EORGui Screening Software is based on the suitability of the oil properties and reservoir characteristics data in the field covering 9 (nine) parameters as follows:
a. Oil API Gravity
b. Oil viscosity
c. Oil Composition
d. Reservoir oil saturation

e. Reservoir formation type
f. Reservoir net thickness
g. Average permeability
h. Reservoir depth
i. Reservoir temperature

These 3 (three) methods are used to do the screening process on 5 (five) different fields. There are two carbonate reservoirs and three sandstone reservoirs with different oil properties. So, the differences between these screening methods/technologies are known.

Result and Discussion

Screening using PertaEOR resulting list of EOR methods. The suitability of 9 oil and reservoir parameters is represented by a match probability score as shown in Figure 1. The match probability score of an EOR method regarding to oil and reservoir data is calculated using an equation involving the multiplication of the probability number per parameter with a weighting factor value. Figure 2 is a ranking of the EOR methods starting from the most suitable to the least suitable in the D fields.

Manual EOR Screening using Al-Adasani & Bai (2010) and Taber et al. (1997) results can be seen in table 3. The suitable EOR method is sorted by the total number of parameters whose values are in the range and the number of parameters whose values are slightly out of the range. All parameters assume equal and there is no penalty score if the input data are too far from the database.

Screening using EORGui software gives results as shown in Figure 2. The results are a spider chart and table of suitability from each parameter with certain EOR methods. The level of compatibility of EOR methods is indicated by dark green, green, and red colors for each parameter. They are sorted according to the match percent value. The correlation between the green, bright green, and red colors is still unknown to the percent match value that appears in spider chat.

In terms of results, it was found that the order of screening between PertaEOR and the literature (manual screening) was quite consistent. Although in the manual screening several EOR methods are included in one group due to the difficulty of sorting if they have the same number of green columns. This does not happen in PertaEOR, because the value has been calculated based on the algorithm that has been compiled. The results of the screening using EORGui also show conformity with PertaEOR, but some EOR methods are not found in EORGui such as miscible gas injection. In fact, if we look at the example in the E field, miscible gas injection ranks first in both manual screening and PertaEOR.

PertaEOR screening results in accordance with study work or implementation in the 5 fields. Field B located in East Java is a carbonate field and understudy of CO2 EOR study align with PertaEOR suggests (figure 1 match probability). Likewise, the A, C, D, & E fields are currently under Chemical EOR study and those are align with the results of PertaEOR screening.

PertaEOR has a complete feature which can accept single-value and distributed value data input. The result is fair since every parameter has a weighting factor based on the database. And if the data is too far from range, the match probability score will be reduced by the penalty algorithm**.**

Conclusions

The results of this study indicate that the technical and statistical algorithm, also penalty algorithm in PertaEOR can produce better output because the process is efficient in terms of computational time compared to manual screening, the results are more reliable because it was objective, quantitative, fair with addition of weighting value and penalty score, and cover almost all types of EOR methods. This method is expected to be one of the solutions to accelerate the EOR program in supporting the target to increase national oil production.

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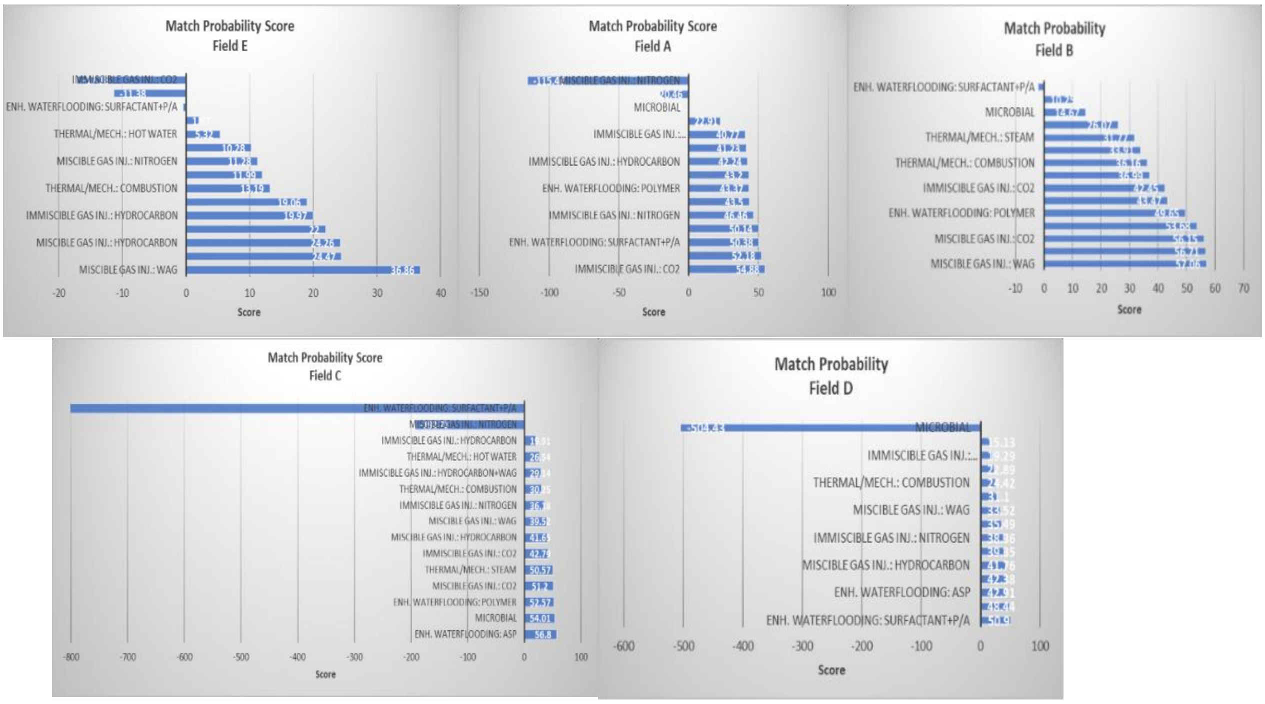

Figure 1: Match Probability Score for each field (A to E) using PertaEOR

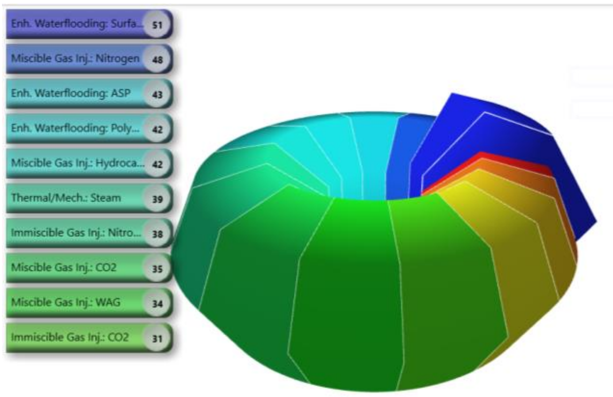

Figure 2: PertaEOR Screening Result on D field

Field Id	Oil Properties			Reservoir Characteristics					
	Gravity (deg API)	Viscosity (cp)	Composition	Oil Saturation (% PV)	Formation Type	Net Thickness (ft)	Average Permeability (md)	Depth (ft)	Temperature (deg F)
A	26.56	5.25	C5-C12	40	Sandstone	26.67	99	3938.92	198
B	40.6	1.42	NC	48.6	Carbonate	114.02	117	5815	235
C	46	0.52	High % C5-C11	48	Sandstone	261.31514	225	2798.5564	141
D	47	0.51	High % C5-C12	59.1	Sandstone	41.33	16.54	2795.28	149
E	32.1-33.3 mean=32.4	0.51-1.13 mean=0.66	High % C5-C12	70-85 mean = 75	Carbonate	947	10-1000 mean=100	4035-4982 mean=4500	263-267 mean: 265

Table 1: Oil and Reservoir Data

Figure 3: Other Software Screening Result on E field

No.	EOR Method	Oil Properties		Reservoir Characteristics						
		Gravity (°API)	Viscosity (cp)	Porosity (%)	Oil Saturation (% PV)	Formation Type	Permeability (md)	Net Thickness (ft)	Depth (ft)	Temperature (°F)
				Miscible Gas Injection						
1	CO2	28[22]-45 Avg. 37	35-0 Avg. 2.1	3-37 Avg. 14.8	15-89 Avg. 46	Sandstone or Carbonate	1.5-4500 Avg. 201.1	[Wide Range]	1500^{a}-13365 Avg. 6171.2	82-250 Avg. 136.3
2	Hydrocarbon	23-57 Avg. 38.3	18000-0.04 Avg. 286.1	4.25-45 Avg. 14.5	30-98 Avg. 71	Sandstone or Carbonate	0.1-5000 Avg. 726.2	[Thin unless dipping]	4040[4000]-15900 Avg. 8343.6	85-329 Avg. 202.2
3	WAG	33-39 Avg. 35.6	0.3-0 Avg. 0.6	11-24 Avg. 18.3		Sandstone	130-1000 Avg. 1043.3	NC	7545-8887 Avg. 8216.8	194-253 Avg. 229.4
4	Nitrogen	38[35]-54 Avg. 47.6	0.2-0 Avg. 0.07	7.5-14 Avg. 11.2	0.76[0.4]-0.8 Avg. 0.78	Sandstone or Carbonate	0.2-35 Avg. 15.0	[Thin unless dipping]	10000[6000]-18500 Avg. 14633.3	190-325 Avg. 266.6
				Immiscible Gas Injection						
5	Nitrogen	16-54 Avg. 34.6	18000-0 Avg. 2256.8	11-28 Avg. 19.46	47-98.5 Avg. 71	Sandstone	3-2800 Avg. 1041.7		1700-18500 Avg. 7914.2	82-325 Avg. 173.1
6	CO2	11-35 Avg. 22.6	592-0.6 Avg. 65.5	17-32 Avg. 26.3	42-78 Avg. 56	Sandstone or Carbonate	30-1000 Avg. 217		1150-8500 Avg. 3385	82-198 Avg. 124
7	Hydrocarbon	22-48 Avg. 35	4-0.25 Avg. 2.1	5-22 Avg. 13.5	75-83 Avg. 79	Sandstone	40-1000 Avg. 520		6000-7000 Avg. 6500	170-180 Avg. 175
8	Hydrocarbon +WAG	9.3-41 Avg. 31	16000 - 0.17 Avg. 3948.2	18-31.9 Avg. 25.09	Avg. 88	Sandstone or Carbonate	100-6600 Avg. 2392		2650 -9199 Avg. 7218.71	131-267 Avg. 198.7
				(Enhanced) Waterflooding						
9	Polymer	13-42.5 Avg. 26.5	4000^{b}-0.4 Avg. 123.2	10.4-33 Avg. 22.5	34-82 Avg. 64	Sandstone	1.8^{e}-5500 Avg. 834.1	[NC]	700-9460 Avg. 4221.9	74-237.2 Avg. 167
10	Alkaline Surfactant Polymer (ASP)	23[20]-34[35] Avg. 32.6	6500^{c}-11 Avg. 875.8	26-32 Avg. 26.6	68[35]-74.8 Avg. 73.7	Sandstone	596[10]-1520	[NC]	2723-3900[9000] Avg. 2984.5	118 [80]-158[200] Avg. 121.6
11	Surfactant + P/A	22-39 Avg. 31	15.6-3 Avg. 9.3	16-16.8 Avg. 16.4	43.5-53 Avg. 48	Sandstone	50-60 Avg. 55	[NC]	625-5300 Avg. 2941.6	122-155 Avg. 138.5
				Thermal/Mechanical						
12	Combustion	10-38 Avg. 23.6	2770-1.44 Avg. 504.8	14-35 Avg. 23.3	50-94 Avg. 67	Sandstone or Carbonate [Preferably Carbonate]	10-15000 Avg. 1981.5	[>10]	400-11300 Avg. 5569.6	64.4-230 Avg. 175.5
13	Steam	8-30 Avg. 14.5	5E6-3^{d} Avg. 32971.3	12-65 Avg. 32.2	35-90 Avg. 66	Sandstone	1^{e}-15000 Avg. 2605.7	[>20]	200-9000 Avg. 1643.6	10-350 Avg. 105.8
14	Hot Water	12 -25 Avg. 18.6	8000-170 Avg. 2002	25-37 Avg. 31.2	15-85 Avg. 58.5	Sandstone	900-6000 Avg. 3346	-	500-2950 Avg. 1942	75-135 Avg. 98.5
				Microbial						
16	Microbial	12-33 Avg. 26.6	8900-1.7 Avg. 2977.5	12-26 Avg. 19	55-65 Avg. 60	Sandstone	180-200 Avg. 190	-	1572-3464 Avg. 2445.3	86-90 Avg. 88
The following reported EOR reservoir characteristics have extreme values that impact the respective average and range in Table 1.										

Table 2: Manual Screening using Al-Adasani&Bai (2010) on C field

		Oil Properties			Reservoir Characteristics					
Detail Table in Ref. 16	EOR Method	Gravity (deg API)	Viscosity (cp)	Composition	Oil Saturation (% PV)	Formation Type	Net Thickness (ft)	Average Permeability (md)	Depth (ft)	Temperature (deg F)
Gas Injection Methods (Miscible)										
1	Nitrogen and flue gas	>35↑ avg: 48↑	<0.4 ↓ avg: 0.2↓	High percent of C_1 to C_7	>40↑ avg:75↑	Sandstone or carbonate	Thin unless dipping	NC	>6,000	NC
2	Hydrocarbon	>23↑ avg:41↑	<3↓ avg:0.5↓	High percent of C_2 to C_7	>30↑ avg:80↑	Sandstone or carbonate	Thin unless dipping	NC	>4,000	NC
3	CO_2	>22↑ avg:36F ↑	<10↓ avg:1.5↓	High percent of C_5 to C_{12}	>20↑ avg:55↑	Sandstone or carbonate	Wide range	NC	>2,500[a]	NC
4	Immiscible gases	>12	<600	NC	>35↑ avg:70↑	NC	NC if dipping and/or good vertical permeability	NC	>1,800	NC
(Enhanced) Waterflooding										
5	Micellar/ Polymer, ASP, and Alkaline Flooding	>20↑ avg:35↑	<35↓ avg:13↓	Light, intermediate, some organic acids for alkaline floods	>35↑ avg:53↑	Sandstone preferred	NC	>10↑ avg:450↑	<9,000↓ avg:3,250	<200↓ avg:80
6	Polymer Flooding	>15	<150, >10	NC	>50↑ avg:80↑	Sandstone preferred	NC	>10↑ avg:800↑ [b]	<9,000	<200↓ avg: 140
Thermal/Mechanical										
7	Combustion	>10↑ avg:16→?	<5,000↓ avg: 1,200↓	Some asphaltic components	>50↑ avg:72↑	High-porosity sand/ sandstone	>10	>50 [c]	<11,500↓ avg:3,500	>100↑ avg: 135
8	Steam	>8 to 13.5→?	<200,000↓ avg: 4,700↓	NC	>40↑ avg:66↑	High-porosity sand/ sandstone	>20	>200↑ avg:2,540↑ [d]	<4,500↓ avg:1,500	NC
NC=not critical.										
NC=not										

Table 2: Manual Screening Result using Taber et al. (1997) on C field

Rank\Field	A	B	C	D	E
	Taber et al. (1997)				
1	Combustion	Combustion	Misc CO2 /Steam injection	Misc CO2 inj/Polymer	Misc CO2 inj
2	ASP Flooding	Misc. CO2 Injection	ASP Flooding	ASP Inj	Combustion
3	Polymer flooding/Miscible CO2 Injection	ASP Flooding	Combustion	Steam	Imsc Gas Injection
4	Immiscible Gas/ Steam Injection	Steam/Imsc. Gas/Misc HC	Polymer Flooding	Combustion	Misc HC inj/Polymer Flooding/ ASP Flooding
5	Miscible HC Injection	Polymer	Imsc. Gas Injection	Imm Gas	Steam Injection
6	N2 & Flue Gas	N2 & Flue gas	Misc HC injection	Mis HC Inj	Misc N2 Injection
7			Misc N2 Injection	Misc N2	
	Aladasani & Bai (2010)				
1	Misc CO2/Steam	Misc CO2 /HC	Misc Co2/Imm N2	Imm N2	Misc CO2/HC
2	Polymer/Combustion	Imm N2/HC-WAG/Polymer	Misc HC/Polymer/Steam	Misc CO2/HC	Imm N2
3	Misc HC/Imm N2	Imm CO2/Combustion/Steam	Imsc CO2/Imsc HC-WAG/ASP	Combustion/Stea m	Imm Co2
4	Imm Co2/ASP	Misc N2	Ims HC/Surfactant/Hot Water	Polymer	Imm HC-WAG/Combustion
5	Imm HC-WAG/Surfactant	Imm HC	Misc WAG/Misc N2/	Imm Co2/ ASP/HC-WAG	Steam
6	Imm HC/Microbial	WAG	Microbial	Misc N2/Imm HC/ Microbial	Polymer
7	Misc WAG/Mic N2	ASP/Surfactant/Hot Water		Misc WAG/Surfactan/ Hot Water	Misc N2
8	Hot Water	Microbial			Immiscible Co2 Injection
9					ASP/Surfactan/WAG/Hot Water

Table 3: Manual Screening Result using Taber et al. (1997) and Al-Adasani & Bai (2010)