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Revisiting EOR Projects in Indonesia through Integrated Study: EOR Screening, Predictive Model, and Optimisation

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Abstract

EOR preliminary analysis is pivotal to be performed at early stage of assessment in order to elucidate EOR feasibility. This study proposes an in-depth analysis toolkit for EOR preliminary evaluation. The toolkit incorporates EOR screening, predictive, economic, risk analysis and optimisation modules. The screening module introduces algorithms which assimilates statistical and engineering notions into consideration. The United States Department of Energy (U.S. DOE) predictive models were implemented in the predictive module. The economic module is available to assess project attractiveness, while Monte Carlo Simulation is applied to quantify risk and uncertainty of the evaluated project. Optimization scenario of EOR practice can be evaluated using the optimisation module, in which stochastic methods of Genetic Algorithms (GA), Particle Swarm Optimization (PSO) and Evolutionary Strategy (ES) were applied in the algorithms. The modules were combined into an integrated package of EOR preliminary assessment. Finally, we utilised the toolkit to evaluate several Indonesian oil fields for EOR evaluation (past projects) and feasibility (future projects). The attempt was able to update the previous consideration regarding EOR attractiveness and open new opportunity for EOR implementation in Indonesia.

Keywords: Integrated EOR Study; Preliminary EOR; EOR Screening; Predictive Model; Economic Analysis; Risk and Uncertainty Evaluation; Optimization; Stochastic Methods; Genetic Algorithm (GA); Particle Swarm Optimization (PSO); Evolutionary Strategy (ES).

1. Introduction

Amongst several categories of fossil resources, oil is one of the most vital. It is crucial to maintaining the continuity of oil production to satisfy energy demands. Nevertheless, there lie considerable challenges to meet this objective since the majority of worldwide oil reservoirs nowadays are mature stage. The

supplementary recovery schemes known as the Enhanced Oil Recovery (EOR) have been proposed to improve oil production from those mature reservoirs to address this issue.

Implementation of EOR technology requires thorough investigations and involves several assessment stages (Dickson et al. 2010; Abu El Ela et al. 2014; Abdurrahman et al. 2016). Figure 1 illustrates the complete EOR assessments workflow. This study focuses on the preliminary assessment stage of EOR. Conducting the primary EOR assessment is at an early stage of EOR analysis to gain prior information regarding feasibility and attractiveness of EOR implementation in the reservoir of interest. This phase commonly incorporates screening, reservoir performance prediction and economic evaluations. Investigators have proposed several different schemes to support this stage of analysis (Al Bahar et al. 2004; Hon et al. 2007; Dickson et al. 2010).

Figure 1. The General EOR Assessment Workflow.

This paper aims to update the previous consideration regarding EOR attractiveness and open new opportunity for EOR implementation in Indonesia. This work proposes a scheme to EOR primary assessment by including risk and uncertainty analysis complemented by optimisation scenario to the general workflow of EOR preliminary screening. EOR screening evaluation is an attempt of identifying the most appropriate EOR method for a given reservoir (Dickson et al. 2010) while simultaneously rule out unfeasible EOR options (Taber et al. 1997a, 1997b).

Figure 2 displays the updated workflow of EOR preliminary screening evaluation proposed by our investigation. A total of five modules, each represents a phase in EOR preliminary assessment, has been developed and linked together into an integrated package. The package is not only capable of assisting engineers to identify EOR feasibility at early stage of analysis, but also establishes better guidance for further assessment stages. The toolkit was used to re-evaluate several oil fields in Indonesia from past projects both success and failure. This endeavour also updates the preceding perspectives about EOR prospect, thus opens a new opportunity to implement EOR in several Indonesian oil fields.

Figure 2. The Proposed EOR Assessment Workflow of Current Study.

2. Methods

2.1. EOR Screening

This study introduces a new procedure to perform EOR screening study by integrating statistical and engineering perspectives. A detailed algorithm could be found in the literature (Hartono et al. 2017). The implementation of the algorithm is built as an in-house software so repetitive works could easily be executed (Hartono et al. 2017).

The initial step of EOR screening evaluation is to construct the selection criteria database which lists the interval of reservoir and fluid properties that likely to yield successful implementation of a particular EOR method (Taber et al. 1997a, Taber et al. 1997b, Dickson et al. 2010, Al Adasani and Bai 2011). The screening criteria was based on combination of the characteristics of successful EOR projects worldwide and understanding of the fundamental mechanisms of oil displacement (Taber et al. 1997a). The methods is to combine the screening criteria reported by earliest literature in EOR database (Taber et al. 1997a, 1997b) with more recent data noted by later database (Al Adasani and Bai, 2010, 2011) in order to develop a thorough database which captures worldwide EOR projects from 1974 until 2010 (See Table A1 in Appendix). We incorporate fifteen EOR methods together with eight reservoir and fluid properties in the database. Table 1 displays the list of reservoir properties included in the study, while the incorporated EOR methods are shown in Table 2.

Table 1. Reservoir and Fluid Properties Incorporated in the Study.

Reservoir and Fluid Properties	Units/Options
Oil API Gravity	°API
Oil Viscosity	cP
Reservoir Porosity	%
Oil Saturation at Initial Flooding Condition	%
Depth	ft
Reservoir Temperature	°F

Reservoir Permeability	mD
Reservoir Formation Type	Options: Sandstone or Carbonate

Table 2. EOR Methods Incorporated in the Study.

EOR Methods Classification	Detailed EOR Methods
Miscible Gas Methods	CO ₂ Hydrocarbon Nitrogen Water Alternating Gas (WAG)
Immiscible Gas Methods	CO ₂ Hydrocarbon Nitrogen Hydrocarbon Water Alternating Gas (HWAG)
Chemical Methods	Polymer Surfactant-Polymer (SP) Alkaline-Surfactant-Polymer (ASP)
Thermal Methods	Steam Flood In-Situ Combustion Hot Water
Microbial Methods	Microbial

The subsequent step is to develop algorithms to assess EOR feasibility. The underlying principle of the algorithms is to consider the relative position of each of the single-valued input properties of the given reservoir against their respective screening criteria of every EOR methods listed in the database. We assume that each of the screening criteria properties listed in the database, with an exception for reservoir formation type property, follows a certain continuous probability distribution form. This premise was the cornerstone of the proposed screening methodology.

Eventually, the EOR methods are ranked in descending order based on their pertinent total fitness scores. Figure 3 demonstrates the general workflow of the proposed screening algorithms. The algorithms were further classified into *single-value* and *distribution-value* input algorithms. Single-value input is the scenario in which the input properties of a given reservoir is in the form of single-value that represents the entire values of the pertinent distribution. A single value of permeability, porosity, oil viscosity, reservoir depth and temperature are instances of single-value input category. We introduced the terms *average*-, *minimum*-, and *maximum*-type property to refer to probability density function (pdf) form: triangle, right-skewed trapezoid, and left-skewed trapezoid respectively ([Hartono et al. 2017](#); also see Figure 4).

Figure 3. The General Workflow of the Screening Algorithm.

Figure 4. The Continuous Distribution Form of the (i) Average-, (ii) Minimum-, and (iii) Maximum-Type.

2.1.1. Screening Algorithm for Single-Value Input

Single-value input is a scenario in which the input properties of a given reservoir may be forced as a single value: permeability, porosity, oil viscosity, reservoir depth and temperature. Integration of statistical and engineering consideration is the science behind it. Figure 4 depicts a graphical conception of the concept. Table A2 of Appendix explicates the default configuration of property classification in screening criteria.

The initial step of the single-value screening algorithms is to determine whether the single-value input property falls within or outside the distribution interval. A *cut-off parameter* α is introduced in order to specify fitness scores to the minimum and maximum values of the distributions, respectively for those properties fall within their respective distribution intervals. A geometrical point of view would have a cut-off value that transforms original distribution into their pertinent pseudo-distribution forms. The pseudo-

distribution forms depend on the respective classification of properties. Figure 5 presents a graphical representation of the notion.

Figure 5. The Cut-Off Parameter and the Pseudo-Distribution Form of the (i) Average-, (ii) Minimum-, and (iii) Maximum-Type.

The *Penalty Factor* PF is acting to counter *cut-off parameter* because PF works for variables fall out of their distribution intervals. The procedure is to honour the distribution classification of average-, minimum-, and maximum-type. Figure 6 delineates the geometrical consideration of the PF procedure.

Figure 6. Graphical Conception of the Penalty Factor Procedure for (i, ii) Average-Type, (iii) Minimum-Type, and (iv) Maximum-Type Properties.

After individual fitness scores have been confirmed, a weighting factor w_i was implemented to each of the individual fitness scores P_i in order to accommodate the relative importance of particular property in a specific EOR method. The more important a particular property in a specific EOR method, the higher the value of the weighting factor. A minimum value of zero and a maximum value of five were determined for the weighting factor value. Table A3 of Appendix summarizes the default value of the weighting factors. The total fitness score TFS for a particular EOR method comes up as presented by Equation 1.

$$TFS_{EOR(k)} = \frac{\sum_{j=1}^8 w_j P(x)_j}{\sum_{j=1}^8 w_j} = \frac{w_1 P(x)_1 + w_2 P(x)_2 + \dots + w_8 P(x)_8}{w_1 + w_2 + \dots + w_8} \quad [1]$$

2.1.2. Screening Algorithm for Distribution-Value Input

Distribution-value input is a case in which the input properties of a given reservoir is in the form of continuous distribution, which characterization depends on the user-selected distribution: uniform, triangular, normal, and lognormal. The underlying principle for the distribution input is to find the points

of intersection between two continuous distributions: screening criteria and input distribution. The individual fitness score was then determined by calculating intersection area of them using Simpson rule. The Newton-Raphson procedure is to obtain the intersection point(s) between the two distribution curves.

This feature is very useful for variables which are always present in a distribution such as porosity and permeability. The typical rock porosity is in lognormal distribution where it is always correlated with permeability in a unique trend named rock type ([Hakiki and Wibowo, 2014](#)).

2.2. EOR Predictive Model

After the most appropriate EOR method has appeared, the subsequent stage is to examine the performance of a particular EOR method in the reservoir of interest. This work deploys a predictive model scheme developed by the United States Department of Energy (U.S. DOE). A total of eight EOR predictive models were included in the study ([U.S. DOE and the Ministry of Energy and Mines of the Republic of Venezuela 1986a, 1986b, 1986c, 1986d, 1986e, 1986f](#); [U.S. DOE and Texaco EPTD 1992](#)). The infill drilling model is available as a supplementary option. Table 3 summarises the available EOR predictive models in our study.

Table 3. EOR Predictive Models Incorporated in the Study.

EOR Predictive Model	Modeled Mechanisms
CO ₂ Miscible Flood Predictive Model (CO ₂ PM)	Miscible CO ₂
CO ₂ -Prophet	Miscible CO ₂ -WAG Immiscible CO ₂
Polymer Predictive Model (PFPM) - Polymer Module	Polymer Flood
Polymer Predictive Model (PFPM) - Waterflood Module	Water Flood
Chemical Flood Predictive Model (CFPM)	Micellar-Polymer (Surfactant-Polymer) Flood Caustic (Alkaline) Flood Caustic-Polymer (Alkaline-Polymer) Flood
Steam Flood Predictive Model (SFPM)	Steam Flood
In-Situ Combustion Predictive Model (ICPM)	In-Situ Combustion
Infill Drilling Predictive Model (IDPM)	Infill Drilling

Additional computer codes were generated to link the predictive modules with other modules in the study ([Hartono et al. 2017](#)). Several objective functions which describe EOR performance are available as options to provide an aggregate information to engineers.

2.3. EOR Economic Analysis

Economics plays a fundamental role in oil and gas industry. EOR is an expensive project and final decision to implement EOR in a certain field often relies more on economics rather than technical aspect ([Taber et al. 1997b](#)). Profit will always be the primary consideration when deciding an EOR implementation. The economic module is linked to the other modules, thus enabling engineers to perform an economical assessment with ease.

The module adapts the Cost Recovery Production Sharing Contract (PSC) system of Indonesia. The toolkit is suitable for assessing an economic aspect of EOR opportunity in Indonesia. The Net Present Value (NPV), Rate of Return (ROR), and Pay-Out Time (POT) are the three available objective variables in the economic module. Spider chart option offers a way to understand the significance of oil price, investment,

and operational costs to the economic attractiveness of a candidate EOR project. EOR price is the most fundamental factor which determines the decision of EOR project. This results are in agreement with the previous study (Taber et al. 1997b).

2.4. EOR Risk Analysis

The risk analysis module is connected to the previous predictive and economic modules, thus allowing engineers to choose technical or financial parameter as the objective variable. Monte Carlo simulation is employed to perform the risk and uncertainty analysis. The procedure is started by specifying the search space of the problem at hand by inserting the minimum, maximum, and average values of particular controllable reservoir properties. The algorithms would select a specific value for every reservoir properties considered by random manner. The respective predictive or economic modules will be run automatically depends on the respective objective variable chosen. The procedure is repeated n times, as many as a number of random simulation to be performed. Important features of the risk and uncertainty would be identified as P10, P50, and P90 on a cumulative frequency graph.

2.5. EOR Optimization Evaluation

Optimization assessment is the final stage of the EOR preliminary assessment of the present study. The primary challenge in performing optimisation evaluation in this study is that the true objective function which relates the response variable and the independent variables of a particular EOR process is unknown and perhaps involving a complicated mathematical formulation. Therefore, the exact optimum solution of EOR process is not possible to be found. Hence, the only solution that is possible to be gained is an approximate solution through numerical algorithms. This approximate solution is also known as the near-optimum solution. In other words, although the most optimum solution may exist, it is hard to find a better solution than the near-optimum solution.

We applied the stochastic methods to find the near-optimum solution of EOR optimisation. Stochastic methods are procedures to find the near-optimum solution of a problem based on random number generation (Ambia, 2012). Certain rules are applied to the random numbers so that they would act as “searching agents” in the defined search space with the objective of finding a near-optimum solution. The procedures did not require the knowledge of the mathematical formulation of the problem (Ambia, 2012), hence they are suitable to be implemented in our EOR optimisation endeavour. Three stochastic procedures of Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Evolutionary Strategy (ES) were implemented in this study. The module was connected to the predictive and economic modules and automatically search the near-optimum solution through the use of one of these previous modules to generate the solution candidates.

3. Results and Discussion

3.1. EOR Screening Evaluations

Implemented algorithm into an in-house software will be tested for some selected field/laboratory cases in Indonesia. There will be three cases of EOR Screening to evaluate and discuss: (1) success projects and recommended by the algorithm, (2) success projects but slightly contradict the algorithm’s results, (3) fail projects and not either supported by the algorithm. We could not find any case of a fail project in which the algorithm expects a successful execution. Table 4 recaps the screening results for selected fields in Indonesia.

Table 4. EOR Screening of Selected Fields in Indonesia.

Reservoir/Fluid Properties	FIELD								
	Tempino	Kenali Asam	Duri	Duri	Minas	Minas	Ledok	Klamono	Handil
Oil Gravity [°API]	43.2	42.2	22.7	22.7	36	36	43	17.5	34
Oil viscosity [cP]	0.9	0.9	100	100	3.5	3.5	7	68	0.6
Porosity [%]	27.1	23.7	36	36	32.3	32.3	34.1	23.4	25.0
Oil Saturation [%]	23	11	10	10	20	20	50	50	20
Depth [ft]	1270	1753	1680	1680	2342	2342	610	929	6070
Temperature [°F]	154.4	154.4	100.4	100.4	199.4	199.4	84.2	125.6	258.0
Permeability [mD]	239	170	500	500	343-1500	343-1500	140	400	10-2000
Formation Type	Sandstone	Sandstone	Sandstone	Sandstone	Sandstone	Sandstone	Sandstone	Carbonate	Sandstone
Application Remarks	Success in Laboratory Scale	Success in Laboratory Scale	Success in Full Field Scale	Failure in Field Trial	Success in Field Trial	Failure in Field Trial	Success in Field Trial	Success in Field Trial	Success in Full Field Scale
Type of Application	Chemical Injection (Surfactant-Polymer)	Chemical Injection (Surfactant-Polymer)	Steam Flood	Chemical Injection (Alkaline)	Chemical Injection (Surfactant-Polymer)	Steam Flood	MEOR	Thermal Induction	Lean Gas Injection
Executing Year	2015	2015	1983-2014	1975	2000	1998	1999	2014	1995-1999
EOR SCREENING RESULTS									
Rank 1	Miscible CO ₂	Miscible CO ₂	Steam Flood	Steam Flood	Immiscible Nitrogen	Immiscible Nitrogen	Surfactant + Polymer	Immiscible CO ₂	Immiscible Nitrogen
Rank 2	Alkaline-Surfactant-Polymer	Immiscible Nitrogen	Immiscible CO ₂	Immiscible CO ₂	Miscible CO ₂	Miscible CO ₂	Alkaline-Surfactant-Polymer	Steam Flood	Miscible CO ₂
Rank 3	Polymer	Miscible Hydrocarbon	Hot Water	Hot Water	Alkaline-Surfactant-Polymer	Alkaline-Surfactant-Polymer	Polymer	Polymer	Miscible Hydrocarbon
Rank 4	Immiscible Nitrogen	Steam Flood	In-Situ Combustion	In-Situ Combustion	Immiscible Hydrocarbon + WAG	Immiscible Hydrocarbon + WAG	Miscible CO ₂	Hot Water Flood	Immiscible Hydrocarbon + WAG
Rank 5	Miscible Hydrocarbon	Polymer	Immiscible Nitrogen	Immiscible Nitrogen	Miscible Hydrocarbon	Miscible Hydrocarbon	Immiscible Nitrogen	Surfactant + Polymer	Immiscible CO ₂
Rank 6	Steam Flood	Hydrocarbon + WAG	Hydrocarbon + WAG	Hydrocarbon + WAG	Polymer	Polymer	Steam Flood	In Situ Combustion	Polymer
Rank 7	Immiscible Hydrocarbon + WAG	Hot Water	Polymer	Polymer	Immiscible CO ₂	Immiscible CO ₂	Hot Water Flood	Immiscible Nitrogen	Miscible WAG
Rank 8	Hot Water	In-Situ Combustion	Alkaline-Surfactant-Polymer	Alkaline-Surfactant-Polymer	Steam Flood	Steam Flood	In Situ Combustion	Immiscible Hydrocarbon + WAG	Alkaline-Surfactant-Polymer
Rank 9	In-Situ Combustion	Alkaline-Surfactant-Polymer	Surfactant + Polymer	Surfactant + Polymer	Hot Water Flood	Hot Water Flood	Immiscible Hydrocarbon + WAG	Microbial	Steam Flood
Rank 10	Immiscible CO ₂	Immiscible CO ₂	Microbial	Microbial	In Situ Combustion	In Situ Combustion	Immiscible CO ₂	Alkaline-Surfactant-Polymer	Hot Water Flood
Rank 11	Miscible WAG	Miscible WAG	Miscible CO ₂	Miscible CO ₂	Surfactant + Polymer	Surfactant + Polymer	Miscible Hydrocarbon	Miscible CO ₂	In Situ Combustion
Rank 12	Surfactant + Polymer	Miscible Nitrogen	Miscible Hydrocarbon	Miscible Hydrocarbon	Microbial	Microbial	Microbial	Miscible Hydrocarbon	Miscible Nitrogen
Rank 13	Miscible Nitrogen	Surfactant + Polymer	Immiscible Hydrocarbon	Immiscible Hydrocarbon	Immiscible Hydrocarbon	Immiscible Hydrocarbon	Immiscible Hydrocarbon	Immiscible Hydrocarbon	Surfactant + Polymer
Rank 14	Microbial	Immiscible Hydrocarbon	Miscible WAG	Miscible WAG	Miscible WAG	Miscible WAG	Miscible WAG	Miscible WAG	Microbial
Rank 15	Immiscible Hydrocarbon	Microbial	Miscible Nitrogen	Miscible Nitrogen	Miscible Nitrogen	Miscible Nitrogen	Miscible Nitrogen	Miscible Nitrogen	Immiscible Hydrocarbon

Compiled from: Hakiki et al. (2015); Subiyantoro, G. (2010); Gael et al. (1994); Hendih et al. (2002); Erlich et al (1997); Abdurrahman et al. (2016); Bou-Mikael et al. (2000); Gunawan et al (2001); Hakiki, F. (2014b); Yusuf et al. (1999); Hakiki et al. (2017); Indonesia, Oil and Gas Fields Atlas of Vol.: 3 (1990), 2 (1991); 4 (1989); 6 (1988); 5 (1991).

Case 1

This case deals with successful projects and also recommended by the algorithm. These fields are highlighted with green in Table 4. This algorithm test confirms that the big three positions are possible to reach successful implementations: laboratory scale (Tempino), field trial (Minas and Klamono), and full field (Duri and Handil).

Tempino is still restricted to laboratory coreflooding where various slugs of surfactant and polymer flood performed (Hakiki et al. 2015) while Minas Surfactant Project has given good results (Bou-Mikael et al. 2000). The first and second position turns out to be a chemical injection. The point of chemical EOR is to reduce interfacial tension σ contributed by surfactant, increase sweep efficiency by polymer and alter wettability by introducing alkaline.

Chemical-based EOR is suited best with minimum depth and temperature because temperature (higher as goes deeper) is crucial to the thermal stability of chemical-agent. Some polymers may be broken (turned to be monomer) as it reaches a limiting temperature. The widely-used polymer in the petroleum industry is polyacrylamide (PAM) or hydrolysed polyacrylamide (HPAM) with the maximum working temperature around 100 °C (~ 212 °F) (Abidin et al. 2012). Some modified or crosslinked PAM or HPAM could work with higher temperature (Abidin et al. 2012; Hakiki, F. 2014a). Therefore, “minimum-type” distribution should address temperature and depth variable. It is suitable for chemical EOR works for light oil and low viscosity because the chemical agent could work as a different phase fluid than oil that is water-phase in which piston-like displacement is desired. Piston like displacement (stable flow) occurs once invading-fluid viscosity μ_{inv} is higher than displaced’s one μ_{disp} (Mobility ratio $M=\mu_{inv}/\mu_{disp}>1$) and capillary number N_{Ca} ($=v_{inv}\mu_{inv}/\sigma$) is also high. (Lenormand et al. 1988).

Heating-based EOR appears in Table 4 as the first suggestion for Duri Field and second suggestion for Klamono as they hold very high oil viscosity. Duri has confirmed to be one of a successful steamflood project in the world while Klamono Field Trial was only still 2 days well heating. Heating-based EOR is practical to reduce viscosity so that the oil will easily flow through porous media and pipe (Hakiki et al. 2017). Some extent effects of heating might alter wettability and reduce oil-water interfacial tension. A viscous oil tends to have higher density (lower API) since heavy components are associated. Heating EOR, thus, outlines with bigger weight and “maximum-type” distribution for viscosity and “minimum-type” for API gravity.

Handil is the least viscous oil in Table 4 and considerably light oil. This condition may call water-based EOR (ASP flood, Polymer flood, Hot Water) and gas-based EOR since it is light and lean oil. Rank 1 to 8 reveals both water and gas-based EOR. It does, however, possess very high temperature 126 °C (~ 258 °F) hence chemical agent may not withstand this heat. Gas-based is, hence, a perfect alternative for this hot reservoir. This research advises a gas injection from Rank 1 to 5. Handil lean gas injection has been promising for three years injection since November 1995 (Gunawan 2001). A lean hydrocarbon gas in light oil reservoir is basically an immiscible process. The gravity drainage of oil handles the primary role, which, in Handil, had already experienced a waterflood treatment.

The residual oil is preserved in tighter pores by interfacial forces in preference to the gas (Sakthikumar et al. 1992). Oil trapped by surface capillary forces is expected being transformed into thin films between gas-water interface when the lean gas is introduced. Gravity or viscous force will then drive the oil films to get produced (Kantzas et al. 1988, Sakthikumar et al. 1992, Gunawan 2001). The existence of low permeability layer in controlled drainage case will allow stabilizing the gas flow and the displacing-gas rate are minute compared to the initial rates in free drainage case and the oil bank is possible to form. Higher initial rates in free drainage case permit oil area is bypassed by the gas front (Kantzas et al. 1988).

Case 2

Case 2 elaborates the successful projects, but slightly contradict the algorithm's results. The fields arise with yellow-highlighted cell in Table 4. The algorithm has a matching case where the lists are out of the big three position. Kenali Asam and Ledok are the samples which stay at 5th and 12th rank for chemical EOR and MEOR, consecutively.

Kenali Asam is almost similar to Tempino but the significant differences are the residual oil and depth as their input. Residual oil is, in fact, vary depends on the area being studied. Kenali Asam results was still on the laboratory scale for various surfactant-polymer slug size flooding ([Hakiki et al. 2015](#)).

MEOR could be considered the last option of EOR because it may take higher cost and longer laboratory study. The study involves the suitability of oil and brine to bacteria and nutrient as well. Bacteria could be cultivated from indigenous bacteria or an external one. The MEOR hardest part is to make sure the microorganisms is evenly distributed throughout the reservoir ([Yen 1989](#)), then ensure the bacteria withstand with high pressure, high temperature, competition with other type bacteria, and predator-prey behaviour with their bioproducts ([Hakiki 2014b](#), [Putra et al. 2017](#)). The use of microbes is to consume and/or transform the high fraction hydrocarbon components to be lower fraction hence the oil gets less dense and less viscous ([Purwasena et al. 2010, 2014](#)). The bioproducts of bacteria: gas, organic acids, solvents, polymer, and/or surfactants are acting like chemical-EOR agents to increase sweep efficiency, alter wettability, and reduce interface energy ([Halim 2015](#), [Halim et al. 2015](#)).

Ledok is the first MEOR project in Indonesia whose oil rate had increased from 8.18 BOPD in 15 July 1999 after injection on 8 July 1999 ([Yusuf et al. 1999](#)). Table 4 suggests that Ledok could be treated with chemical-based EOR from 1st to 3rd rank. The successful of MEOR implementation could be justified since the MEOR mechanism is similar to chemical-based EOR.

Case 3

The last case is about to discuss fail projects and not either supported by the algorithm. Red-highlighted cells indicate this group. Duri and Minas field has already been discussed in the Case 1. This lesson learnt is to unveil that our algorithm is robust to predict the EOR method suitability. It is not only statistically speaking but also EOR mechanism-based explanations could in-depth cover these failures.

Case 1 undergoes that the best options to execute in the laboratory, field trial, full field lies on the three best offers. Case 2 opens a thought that similar EOR mechanism may be in the different form of EOR suggestion. MEOR is more likely related to Chemical-EOR. It needs more extreme real field data to elaborate the case. The slightly-missed ranking may be due to the limited database, in which dynamic update of the database is required.

3.2. Advance Studies

Revisiting Minas Field

We selected Minas Field as the first case to be evaluated by our EOR preliminary assessment toolkit with detailed properties served in Table 5. Minas is a giant oil field located in the central Sumatra basin of Indonesia. The field has been identified as one of the largest oil fields in Southeast Asia with an estimated original oil in place of 9 billion barrels ([Bou-Mikael et al. 2000](#)). Until the year of 2000, Minas has produced up to 4.2 billion barrels of oil ([Bou-Mikael et al. 2000](#)). It was also estimated that around 4.5 billion barrels of remaining oil was available in Minas for the target of EOR technology ([Bou-Mikael et al. 2000](#)). Several EOR field trials have been attempted at the particular field since the year of 2000. It has

been identified that implementation of chemical flooding, especially the surfactant-polymer (SP) flooding, produced promising oil recovery (Bou-Mikael et al. 2000; Masduki et al. 2010).

Table 5. Input for Predictive and Optimisation Module: Case Study of Minas Field.

Properties	Value	Unit
Pattern Area	4.3	[acres]
Current Reservoir Pressure	450	[psi]
Oil FVF	1.08	[bbl/STB]
Water FVF	1.003	[bbl/STB]
Water Salinity	2465	[ppm]
Remaining Oil in Place for 1 Pattern	0.2795	[MMSTB]
Surfactant Concentration (of PV)	0.02	[]
Surfactant Slug Size (of PV)	0.25	[]
Polymer Slug Size	0.5	[]
Pattern Injection Rate	950	[bbl/day]

Table 6 expresses the summary of reservoir performance evaluation of Minas field. Early reservoir performance assessment based on the true flooding design provided cumulative oil production of 19.5 MSTB for total injection period of 160 days. Meanwhile, the record of true surfactant-polymer field trial at Minas showed a higher cumulative oil production of 62.44 MSTB in a far shorter injection period of 7.4 days. The discrepancy is due to the fact that the U.S. predictive models were conservative models, which means that their predictive outcomes would tend to be lower than the real situation.

Table 6. Predictive Model Outcomes for Minas Field and Its Comparison to the True Results.

Predictive Model Result		Minas Field Trial True Result	
Time Period [Days]	Cumulative Oil Produced [MSTB]	Time Period [Days]	Cumulative Oil Produced [MSTB]
60	0	0.51	4.91
90	5.8	3.52	33.71
120	14.5	6.16	52.78
160	19.5	7.42	62.44

Based on the premise that the target oil (remaining oil in place) of the pattern is approximately 280 MSTB, the cumulative oil production of the predictive model and the true field trial represented 7% and 22.2% recovery factors (RF), respectively. The discrepancy could be minimised by performing optimisation study. Table 7 conveys the result from optimisation evaluation. Particle Swarm Optimization (PSO) procedure yielded the highest cumulative oil production than the other two schemes, hence it was chosen as the optimum design.

Table 7. Results from Optimization Module for Minas Field Assessments.

Stochastic Method	Cumulative Oil Production [MSTB]
Genetic Algorithm	27.7
Particle Swarm Optimization	27.9
Evolutionary Strategy	27.8
Optimum Scenario: Particle Swarm Optimization	
Controllable Factors	Level of Controllable Factors
Surfactant Concentration []	0.014
Injection Rate [bbl/day]	745
Surfactant Slug Size (of PV) []	0.4
Polymer Slug Size (of PV) []	0.5

Table 8 demonstrates that the optimisation study surfactant-polymer flood ameliorates cumulation oil production up to 27.9 MSTB from the initial value of 19.5 MSTB. This is equivalent to 10% RF. Although this value is still below the true value of Minas trial flood, the discrepancy between the predicted and true value was successfully reduced. This confirms the objective of optimisation evaluation.

Table 8. Optimization Study of Cumulative Oil Production.

Predictive Model Result: Optimum Scenario	
Time Period [Days]	Cumulative Oil Produced [MSTB]
91.25	0
182.5	16.5
273.75	25.7
299.3	27.9

Economic assessment of the project revealed that oil price and investment are two parameters which significantly affect the economic feasibility. Risk assessment result is summarised in Table 9, in which the P50 and P90 of the project were displayed. Figure A1 to A4 of the appendix expose the screenshots of the assessments.

Table 9. Outcomes from Risk Analysis of Minas Field.

Risk Parameters	Cumulative Oil Production [MSTB]	Variables	Values
P50	15.79	Polymer Slug Size (of PV) []	0.262
		Pattern Injection Rate [bbl/day]	287
		Surfactant Concentration []	0.018
		Surfactant Slug Size []	0.235
P90	21.04	Polymer Slug Size (of PV) []	0.325
		Pattern Injection Rate [bbl/day]	630
		Surfactant Concentration []	0.025
		Surfactant Slug Size []	0.289

Revisiting Duri Field

Duri field is the second largest oil field in Indonesia in terms of the original oil in place. It is also the largest full-field steam flood project in the world (Gael et al. 1994, 1995). The field is located in Riau Province of Central Sumatera approximately 120 km northwest from Pekanbaru (Gael et al. 1994). It is intriguing to investigate this field through our toolkit and see the obtained results.

It is interesting to mention that the other thermal methods were listed in the top four of the rank. Reservoir performance prediction study was performed only on the Pertama and Kedua sands of the Duri field. The two sands have the largest contribution to the oil production of the field. It was estimated that the Pertama and Kedua field contains up to 4.1 billion barrels of original oil in place. With a total developed area of 15,100 acres, each flooding pattern contributed to 15.5 acres. The predictive model yielded approximately 6.8% of recovery factor from the steam flooding process. This value is in close agreement with the true reported recovery factor of 7.4%. Economic analysis showed favourable outcome, although the economic attractiveness of the project would depend heavily on oil price and injection cost. Since steam injection rate was the only controllable factor in the study, optimisation evaluation could not be performed because the module would require minimum two controllable factors to define the search space.

4. Concluding Remarks

The algorithm has a robust chance to assist engineer(s) seeing EOR methods possibility from limited reservoirs properties: oil gravity, oil viscosity, porosity, residual oil saturation, depth, temperature, permeability, and rock type.

The EOR screening developed from combining statistical and physical meaning (introduced through weight parameter w_i) has confirmed intense results with respect to the previous projects in Indonesia.

The integrated algorithm links EOR screening, predictive model, economic analysis, risk analysis, and optimisation evaluation, which is a strong consideration prior to applying at least laboratory study; which can later be extended to a pilot project.

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Appendix

Table A1. The Established Screening Criteria Database.

EOR Methods	Reservoir and Fluid Properties																						
	Oil API Gravity (°API)			Oil Viscosity (cP)			Porosity (%)			Oil Saturation at Initial Flooding (%)			Depth (ft)			Temperature (°F)			Permeability (mD)			Formation Type	
	Min	Avg.	Max	Min	Avg.	Max	Min	Avg.	Max	Min	Avg.	Max	Min	Avg.	Max	Min	Avg.	Max	Min	Avg.	Max	S*	C**
Miscible CO2	22	36	45	0.3	1.65	35	3	14.8	37	15	52.75	89	1500	6171.2	13365	82	136.3	250	1.5	201.1	4500	1	1
Miscible Hydrocarbon	23	40	57	0.04	134.3	18000	4.25	14.5	45	30	76.5	98	4000	6191.8	15900	85	202.2	329	0.1	726.2	5000	1	1
Miscible WAG	33	42	39	0.07	0.175	0.4	11	18.3	24	40	75	80	6000	9108.4	18500	194	229.4	253	130	143.3	1000	1	1
Miscible Nitrogen	35	48	57	0.07	0.2	0.4	7.5	11.2	14	40	75.75	80	6000	12316.65	18500	190	266.6	325	0.2	15	35	1	1
Immiscible Nitrogen	16	41	54	0	2256.8	18000	11	19.5	28	35	70.5	98.5	1700	7914.2	18500	82	173.1	325	3	1041.7	2800	1	1
Immiscible CO2	11	22	35	0.6	65.5	600	17	26.3	32	15	63	78	1150	3385	8500	82	124	198	30	217	1000	1	1
Immiscible Hydrocarbon	22	38	48	0.25	2.1	4	5	13.5	22	35	74.5	83	6000	6500	7000	170	175	180	40	520	1000	1	1
Immiscible Hydrocarbon + WAG	9.3	34	41	0.17	3948.2	16000	18	25	31.9	35	70	83	2650	7218.71	9199	131	198.7	267	100	2392	6600	1	1
Polymer Flood	13	33	43	0.4	111.6	4000	10.4	22.5	33	34	72	92	700	6610.95	9600	74	153.5	237.2	1.8	817.05	15000	1	0.5
Alkaline-Surfactant-Polymer (ASP) Flood	20	33	35	11	444.4	6500	26	26.6	32	35	63.35	74.8	500	3117.25	9000	80	119.8	200	10	486.5	1520	1	0.5
Surfactant + Polymer/Alkaline Flood	20	33	39	3	11.15	35	16	16.4	16.8	43.5	48	53	625	3095.8	9000	122	138.5	155	10	55	60	1	0.5
In-Situ Combustion	10	20	40	1000	1200	5000	14	23.3	35	50	69.5	94	400	5569.6	11500	64.4	155.25	230	10	1033.25	15000	1	0.5
Steam Flood	8	13.5	27	10	18835.65	5000000	12	32.2	65	35	66	90	200	1571.8	4500	10	175	350	1	2572.85	15000	1	0.5
Hot Water Flood	8	16	27	10	3351	200000	25	31.2	37	15	62.25	85	500	1721	4500	60	98.5	280	200	2943	6000	1	0.5
Microbial	12	26.6	33	1.7	2977.5	8900	12	19	26	55	60	65	1572	2445.3	3464	140	150	160	180	190	200	1	0

Note:

*Sandstone

**Carbonate

Table A2. Default Configuration of Property Classification of the Screening Criteria.

Criteria/EOR Methods	Oil API Gravity	Oil Viscosity	Reservoir Porosity	Oil Saturation at Initial Flooding Condition	Depth	Reservoir Temperature	Reservoir Permeability
Miscible Gas Inj.: CO ₂	Maximum	Minimum	Maximum	Maximum	Maximum	Minimum	Maximum
Miscible Gas Inj.: Hydrocarbon	Average	Minimum	Maximum	Maximum	Average	Average	Maximum
Miscible Gas Inj.: WAG	Average	Minimum	Maximum	Maximum	Average	Average	Maximum
Miscible Gas Inj.: Nitrogen	Maximum	Minimum	Maximum	Maximum	Average	Average	Maximum
Immiscible Gas Inj.: Nitrogen	Average	Minimum	Maximum	Maximum	Average	Average	Maximum
Immiscible Gas Inj.: CO ₂	Minimum	Minimum	Maximum	Maximum	Average	Average	Maximum
Immiscible Gas Inj.: Hydrocarbon	Minimum	Minimum	Maximum	Maximum	Average	Average	Maximum
Immiscible Gas Inj.: Hydrocarbon + WAG	Average	Minimum	Maximum	Maximum	Average	Average	Maximum
Polymer	Maximum	Minimum	Maximum	Maximum	Minimum	Minimum	Maximum
ASP	Maximum	Minimum	Maximum	Maximum	Minimum	Minimum	Maximum
Surfactant + Polymer/Alkaline	Maximum	Minimum	Maximum	Maximum	Minimum	Minimum	Maximum
Thermal/Mech.: Combustion	Minimum	Minimum	Maximum	Maximum	Average	Minimum	Maximum
Thermal/Mech.: Steam	Minimum	Minimum	Maximum	Maximum	Minimum	Minimum	Maximum
Thermal/Mech.: Hot Water	Minimum	Minimum	Maximum	Maximum	Minimum	Minimum	Maximum
Microbial	Average	Minimum	Maximum	Maximum	Average	Minimum	Maximum

Table A3. Default Configuration of the Weighting Factors w_i .

Criteria/EOR Methods	Oil API Gravity	Oil Viscosity	Reservoir Porosity	Oil Saturation at Initial Flooding Condition	Depth	Reservoir Temperature	Reservoir Permeability	Reservoir Formation Type
Miscible Gas Inj.: CO ₂	3	1	1	1	1	1	1	1
Miscible Gas Inj.: Hydrocarbon	1	1	1	1	1	1	1	1
Miscible Gas Inj.: WAG	1	1	1	1	1	1	1	1
Miscible Gas Inj.: Nitrogen	1	1	1	1	1	1	1	1
Immiscible Gas Inj.: Nitrogen	1	1	1	1	1	1	1	1
Immiscible Gas Inj.: CO ₂	3	1	1	1	1	1	1	1
Immiscible Gas Inj.: Hydrocarbon	2	1	1	1	1	1	1	1
Immiscible Gas Inj.: Hydrocarbon+WAG	1	1	1	1	1	1	1	1
Enh. Waterflooding: Polymer	1	1	1	1	3	3	1	1
Enh. Waterflooding: ASP	1	1	1	1	3	3	1	1
Enh. Waterflooding: Surfactant+P/A	1	1	1	1	3	3	1	1
Thermal/Mech.: Combustion	3	3	1	1	3	1	1	1
Thermal/Mech.: Steam	3	3	1	1	3	1	1	1
Thermal/Mech.: Hot Water	3	2	1	1	3	1	1	1
Microbial	1	1	1	1	1	3	1	1

Figure A1. Results of Screening Study of Minas Field

(i)

(ii)

Figure A3. Results from (i) Economic and (ii) Risk Evaluation Study of Minas Field

(i)

(ii)

Figure A2. Results of Surfactant-Polymer Predictive Model for Minas Field, (i) Original Scenario, (ii) Optimized Scenario

Figure A4. Results of Optimization Assessment of Minas Field