**EOR Advisor System: A Comprehensive Approach to EOR Selection**

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**Abstract**

Hydrocarbon exploration is reaching global frontiers in the search for near- and long-term solutions to increase oil production from the existing assets. Enhanced oil recovery (EOR) offers a substantial alternative to improve recovery from existing and mature fields by means of enhancing pore level sweeping in the reservoir.

While the principles of EOR are not new, field implementation has been scarce and as a consequence, the physics governing the displacement process have not been completely understood, nor has the screening criterion been properly defined. Several authors have proposed different binary approaches to address the issue of screening, with the drawback of different, and in some cases, contradictory screening results.

This paper presents a workflow to assess the EOR applicability for a given reservoir. The backbone of the advisor system is an expert system that has been calibrated using information from a systematic data review of a newly developed global EOR project database, merged with in-house EOR engineering expertise. One of the advantages of this approach over other published EOR expert systems is the capability for handling uncertain input, which enables qualitative ranking of the applicability of various EOR methods in heterogeneous reservoirs. Moreover, the workflow makes it possible to interrogate the expert system with incomplete input information and obtain consistent results, which enables comparative sensitivity runs to assess the most valuable additional information needed to resolve ambiguities in the EOR method ranking. The system is equipped with a comprehensive evaluation of the current static and dynamic conditions of the reservoir, and is fully linked to geological and geophysical modeling and simulation, enabling the extraction of geological-consistent input values for the expert system directly from the model to facilitate quick forecasts of highly ranked EOR methods through surrogate reservoir models.

**Introduction**

EOR screening has been discussed in different levels of complexity by different authors with different approaches postulated, ranging from applicability ranges, binary selection, data mining, and numerical simulation. Simplicity and repeatability are among the traded values during the first attempts of recognizing the best-suited EOR process for a given field, which of necessity, has increased the value of past experiences to guide and provide a "sanity check" for any EOR decision, particularly when dealing with scarce information.

The screening, or selection, is a data-driven process, with the analysis details being proportional to the quality and relevance of the available information and often yielding multiple equally plausible EOR alternatives for a given field. EOR selection requires a proper understanding of reservoir architecture and dominant reservoir fluid-flow forces, making the screening process highly dependent not only on local compatibility (pore level) but also heterogeneity variations on the 3D space. A proper balance of capillary, gravity, and viscous forces during the EOR process becomes an important aspect of the field design, and subsequently of the screening process.

This paper presents a new approach to aid in the EOR selection where a guided, data-driven process was developed to provide qualitative and quantitative estimations of the potential benefits of the main EOR techniques...
for a given reservoir, including dual-porosity naturally fractured reservoirs. The process relies on a combination of an expert system, developed and calibrated with a comprehensive public EOR project database augmented with in-house EOR expertise for the first stages of screening or cases where data are scarce, and a fully comprehensive analysis of the current conditions of the field to determine local, areal, and vertical sweep efficiencies under realistic reservoir heterogeneities. Decisions within the advisor are guided, including a clear statement of results reliability and data uncertainty, ensuring consistency in the results as well as faster, repeatable analysis.

**EOR Database**

Past and present EOR experience is consistently used during any EOR screening process; empirical tables (and ranges) have their origins on past successes and/or failures resulting from the application of a given EOR method under specific field conditions. Analog methods are widely used to further validate the EOR selection and potential recovery factors, increasing the value and the need of a consistent/comprehensive global EOR application database. Due to its nature, published EOR data are scarce; however, as projects mature, the specific EOR information begins to be made public (as in the case the USA and Canada).

Recognizing the value of compiling and analyzing past EOR projects’ experience, public EOR project data were collected from different sources[14-20, 33-50] with information from as early as 1986. A total of ~6,700 entries were initially collected, including all major EOR projects in both clastic and carbonate reservoirs. A preliminary raw data review was made to eliminate duplicate entries, mislabeled information, name change of projects, etc., reducing the total number of projects to ~2,800. Fig. 1 shows the EOR project history for clastic reservoirs, where, as expected, thermal methods have consistently been active through the 1990s period of low oil prices, whereas immiscible hydrocarbon projects have constantly decreased. Miscible CO₂ projects of interest are starting to be more prolific. A similar trend can be observed in the carbonate reservoirs where CO₂ and hydrocarbon miscible are dominant.

![Active EOR Projects](image)

**Fig. 1—EOR project history in clastic reservoirs**

Details of information in the database vary according to the source and operator. Efforts were made to maintain a consistent baseline with at least seven key entries for all of the projects so that information can be easily accessed and processed. Decisions on the key entries were made based on previous in-house EOR screening experience as well as a statistical analysis of the parameters to identify trends, ranges, and dependencies within each individual EOR method. Fig. 2 shows the viscosity distribution for the available EOR projects on a log scale. As expected, dependencies are clearly shown with thermal/chemical projects selected for the higher end viscosity values and miscible/immiscible for the lower viscosity projects.
The dependencies between API gravity, viscosity, and temperature are shown in Fig. 3, and indicate a clear relationship can be observed.

Upon reviewing and validating the main EOR methods dependency and maintaining consistency with the published literature ranges, seven parameters were identified as being key on the identification and ranking for the applicability of one of the EOR methods onto a particular reservoir. Seven parameters were short listed for the selection, namely:

- Oil gravity, °API
- Oil viscosity, cp
- Reservoir depth, ft
- Reservoir temperature, °F
- Porosity, %
- Permeability, md
- Formation type

The interdependencies between some of the selected parameters, such as reservoir depth and temperature, are well understood, but were kept in the analysis to preserve back compatibility with the previous literature publications on EOR screening. Other interdependencies such as oil gravity-viscosity and porosity-permeability follow a general trend but are still required to be defined separately to preserve the predictability of the advisory.
system. Finally, the ranges of applicability (based on this analysis) were compared and validated with the existing published and internal screening criterion.

**Expert System Setup**

After a rigorous review and statistical analysis of the EOR data available, the expert system setup began to capture the findings from previous in-house studies and further investigations of the data in the database. Because of the fact that the data were often incomplete and came with high uncertainty (e.g., one viscosity value for an entire reservoir), an expert system algorithm had to be selected that could deal with the uncertainty and incomplete input data.

The authors selected the Bayesian belief network (BBN) for this task. The reason for this decision is because the EOR selection is a complex approach where the expert opinion has a strong impact on building the logic while the significance of the observations are managed during the building of the expert system. BBNs are a perfect vehicle for this application due to the following features:

- BBNs are fully transparent and turn implicit knowledge through a quantification of the reasoning logic and a graphical representation into explicit knowledge; hence, a great tool for communicating uncertain and imprecise knowledge to other experts and are therefore an enabler of collaboration in teams.
- BBNs are capable of reasoning under uncertainty, which corresponds much more to the way a human being reasons. Observations are usually expressed probabilistically than deterministically, such as the gas content in the reservoir fluid is rather high. Deterministic- and rule-based explanation tools, very much in contrast to Bayesian networks, will have difficulties combining the imprecise information from various sources under a common, consistent, and unbiased reasoning umbrella.
- Gaps in, imprecise, or even incorrect measurements do not impair the inference capabilities of the Bayesian networks, because lacking any hard or reasonable facts (measurements), they assume the most likely value based on the formulation of prior probabilities.
- The reliability of expert systems based on Bayesian networks is very high. The computation of posterior probability is quick and can be performed in a stable manner, even in combination with larger workflow systems in distributed systems (e.g., in a large information technology environment).
- The stored logic in a Bayesian network is adaptable by various learning algorithms or through manual intervention. The logic can be modified incrementally whenever new pieces of information, such as new observations, are available that are significant and generalized enough to be included in the expert system.
- Due to the structure of Bayesian networks, it is possible to easily combine the knowledge from various domains. While conventional decision making in asset teams is typically very isolated with every domain, drawing decisions based on their relevant evidences only, Bayesian networks enable the integration of all expert branches under a joint decision support system, which enables consistent screening and interpretation of evidences.

These points make Bayesian networks an ideal reasoning and explaining engine in automated but human-centered workflows. While automating repetitive and obvious tasks, the human expertise is still consulted if the situation demands clarification. This approach is a necessary concept to assist in EOR decision making in an optimal way by supporting the engineering team where possible and giving full responsibility and flexibility to them, when human expertise is necessary to integrate all information, impressions, and experiences. Using Bayesian networks as the reasoning engine, the decision-making workflow can be a fully automated process, while only requesting user guidance during ambiguous situations or when additional information is needed to draw a more definite decision.

The initial setup of the BBNs needs to be performed by the experts. In the work being presented, this was available from a rigorous literature research as well as in-house expertise. The authors chose to use a 5-step process to set up the BBNs:

1. Establish BBNs with ranges and logic derived only from literature—the process begins with setting up the Bayesian networks using expert knowledge only; i.e., the prior knowledge that sets the foundation for the expert system. A rigorous literature research and in-house discussions were performed to derive the initial ranges and logic. For each EOR method, nodes, ranges, and probabilities were defined. Each node represents a relevant input value, a parameter, and each range denotes the range of values that are considered high, medium, or low for any of the given parameters. The list of significant input parameters for the various EOR methods as well as the resulting ranges for CO₂ miscible EOR projects are presented in Table 1 and Table 2.
Table 1—Node selection for each EOR method with some parameters not critical for certain EOR methods

Ranges define the states or values of these parameters and were obtained from the literature. The probability tables are set so that projects having values within these ranges are modeled to be 100% applicable. These ranges along with the logic were used as the starting point to set up the Bayesian networks.

Table 2—CO₂ screen ranges for miscible projects; the last row shows a comparison of literature ranges and ranges derived from the database

2. Cross validate binary logic from literature with available data (EOR observations)—the logic derived from the literature was cross checked against the database projects. The total list of EOR projects considered was 2,781, 2,332 of which were labeled as successful (without a clear description or unified definition of successful). A so-called confusion matrix, set up to identify the quality of the BBN inferences, showed how many successful projects were classified by the BBNs as successful and vice versa and how many projects were not properly classified. Projects that were not correctly classified were investigated in more detail to question the ranges from the literature or the available data.

3. Recalibrate BBNs manually as well as using BBN learning algorithms to adapt expert logic with 80% of the observed data—Using the validated and successful data from the EOR database, the BBNs were reviewed and the input ranges were updated to align with the ranges that were observed in the database. This step was necessary to focus the BBNs in preparing the next step that will update the logic according to the data in the database.
4. Update the BBN logic—Using BBN training algorithms, the successful EOR projects were incorporated into the BBN algorithm. The BBN uses a counting-learning algorithm to update the internal logic. The expert can control the degree by which data are considered to account for uncertainties (e.g., low degree of consideration for data from more questionable sources). The learning algorithm includes the data from the database and modifies the expert system that so far has only been calibrated with the literature data. This method allows the underlying logic (provided by the experts and from the literature research) to be maintained while the logic is adjusted for the actual observations in the field. The BBNs therefore can emulate the decisions of experts and learn as new findings are provided.

![Fig. 4—Value ranges distribution for depth](image)

5. Blind test BBNs with remaining 20% of the data set—To ensure further validity of the BBNs, blind tests were performed. Again a confusion matrix was set up. The logic showed an increase in reliable
results for cases where a large amount of literature information and data were available. This reliability is tracked and indicated to the user so that the results can be questioned when necessary.

**EOR Screening Approach**

As detailed and useful as the analysis of present and past experience is, it only provides a qualitative guidance on the EOR potential. Database entries are often ambiguous and subjective (such as in the definition of “successful” or “unsuccessful” projects). Furthermore, the database is lagging in time as data can only be considered after the effect of any selected EOR method has been observed and reported by the operators, which can take a considerable amount of time. This analysis is especially tricky if a completely new EOR method was used. In this case, sufficient sample data are not available nor do we have extended performance history to allow for a somewhat unbiased classification of EOR success. The BBN’s approach of using expert opinion can be beneficial; however, reliability of the expert system increases only with many observations.

As a result, the screening was augmented by introducing a guided system to complement the ranking of the expert system, quantify potential increase displacement (at the pore level), and, subject to data availability, incorporate 3D heterogeneity into the decision process. Four sequential stages were defined within the advisor system. Being a data-driven process, the first two stages were designed to read, audit, and interpret relevant EOR data. The third stage performs a simple yet robust screening of the viable EOR techniques (suitable for most data sets). In the fourth stage, numerical modeling is used to further rank the EOR selection under representative reservoir heterogeneity. **Fig. 6** shows the general approach used for screening by the EOR advisor system.

![Fig. 6—Overall screening workflow](image)

Concentrating on specific EOR processes, data analysis, and validation modules allow for identifying incomplete/inconsistent datasets. These modules are used at a later stage to test the robustness of the selection under displacement uncertainty. These two modules also provide, when data are available, an insight into the reservoir architecture and fluid flow, identifying unswept areas and matching them with the 3D rock-quality distribution to aid in the EOR selection during the first-stage screening. The analysis also involves the qualitative evaluation of the magnitude of recovery mechanisms in matrix and fracture systems (for the naturally fractured reservoir (NFR) cases) such as gravity drainage. Matrix-fracture connectivity and storage are also evaluated and used to guide the EOR selection.

**First-Stage Screening**

Recognizing the limitations and challenges of using separate EOR screening approaches, four screening criteria were defined to complement different analysis methods and allow for a simple yet robust EOR identification in cases where data are scarce. The previously discussed expert system provides a qualitative ranking of the applicable EOR methods based on expert knowledge and past experience (EOR database). This first-stage screening also considers high-level rock-fluid compatibility, local displacement efficiencies for every EOR method, and reservoir architecture, based on internal developed logic for the EOR selection. A typical result of the first-level screening is shown in **Fig. 7**, highlighting the basis for the qualitative and quantitative ranking estimations.
Naturally Fractured Reservoirs

Naturally fractured dual-porosity reservoirs require a combined analysis of two porous media, namely matrix and fractures. Several authors have discussed the dual nature of NFRs and have classified these reservoirs as a function of the storage/transmissivity of either porous media onto different classes\(^\text{30}\). The classes range from fracture-dominated reservoirs, where matrix contribution to both storage and transmissivity is marginal, to reservoirs that behave in a matrix dominated way, where fractured systems act as a permeability enhancement to the matrix and marginally contribute to the overall system storage. Furthermore, recovery mechanisms are different from those of the single-porosity reservoirs, with matrix-fracture component being key to the recovery of fluids (for the mixed matrix/fracture reservoirs), making the more important consideration a proper balance between capillary, gravity, and viscous forces.

This complex behavior of a NFR posed a challenge to the screening because it is difficult to develop a screening process that is able to assess the pore-level displacement efficiency on matrix and fractured systems combined. Especially when considering the relevant recovery mechanisms, including gravity drainage and effectively incorporating the matrix-fracture exchange area (shape coefficient), it becomes apparent how difficult it is to provide recovery estimation for an NFR system. This challenge was solved by implementing a novel workflow that allows for a robust estimation of the EOR potential for matrix-fracture systems combined by using representative mechanistic numerical models. Fig. 8 shows an example of a mechanistic NFR local displacement efficiency prediction.

Fig. 7—First-level screening results sample

Fig. 8—NFR recovery estimate

Compatibility and reservoir architecture (macroscale filtering) logic was also updated to reflect the desirable processes depending on the matrix/fracture storativity/transmissivity balance. Analysis details will be discussed
Second-Stage Screening
Upon completion of the first-stage screening, and considering that the reservoir forces, hydrocarbon saturation distribution, and historical field data have been reconciled during the data analysis stage, the following step quantifies the displacement efficiency of each EOR method under realistic field heterogeneity conditions. This process poses a challenge, given the heterogeneity (at EOR-relevant scale) of the reservoirs as well as the numerical model resolution. Analytical methods alone do not fully encompass the full reservoir heterogeneity; however, when used in conjunction with numerical models, they allow for a better understanding of pore, vertical, and areal potential sweep efficiency. A combination of analytical and numerical methods are used within the advisor; analytical methods provide local displacement efficiency (LDE) estimations and are used as a base for the numerical simulations (data driven) where volumetric displacement efficiency, incremental resources, EOR agent use, and high-level economics are calculated for each viable EOR method.

Representative Reservoir Sampling
Representative sampling of the reservoir heterogeneity becomes a key feature for the displacement efficiency estimation, requiring a proper understanding of static and dynamic distributions (porosity, permeability, pore throat, pressure, saturation, etc.) at the time of the analysis, under the assumption that the existing reservoir model adequately provides such information. A novel workflow was developed to identify, rank, and analyze suitable areas in the reservoir for the investigation, where users can understand the heterogeneity level, moveable oil saturation distribution, size (areal) of each element (representative reservoir element (RRE)), and its relation with the overall formation. The process aims to sample two end members of the EOR potential, one where connectivity and dynamic conditions are favorable for the EOR displacement and another where these are challenges. By individually optimizing the viscous-gravity and capillary forces of each EOR method on either RRE, a representative range of potential EOR incremental benefits may be quantified and used to substantiate the EOR selection under technical and economical premises. Fig. 9 shows an RRE selection example for small area spacing.

Each EOR technique requires an independent optimization process to balance capillary, gravity, and viscous forces on each RRE; thus, ensuring reservoir conformance. Furthermore, the balance and efficiency are also a function of spacing (injector-producer), resulting in a computationally demanding exercise that can be reduced by making full use of the analytical results to estimate concentrations, injection cycles, etc. By combining both approaches, an overall reduction in optimization as high as 50% on selected cases was observed. The results of the individual EOR optimization runs are shown in Fig. 10 with several key performance indicators to not only rank but also help understand the displacement mechanism on each RRE. Displacement efficiency can be used as an overall ranking parameter, accounting for the changes of liquid hydrocarbon on the RRE as result of the EOR agent injection, followed by pore volume injection and cumulative displaced hydrocarbon among others. Before looking into the economic implications, and therefore viability of each method, it is necessary to evaluate the optimized displacement results with the assumptions made during the first-stage screening, namely effect of rock quality on the displacement, particularly channeling and preferential sweeping of the top/bottom reservoir. The advisor allows for displaying the volumetrical sweeping efficiency in a 2D fashion (see Fig. 10) where initial...
vs. final saturation conditions are plotted side-by-side. Furthermore, the display also shows the optimized boundary conditions for the flow and optimum pore-volume injection.

With the technical potential (quantitative ranking) understood, the next step is to analyze the economical robustness of each EOR technique, considering the EOR agent use, injection, production costs, as well as oil and gas prices. This simple economic analysis can be used to rank the EOR methods further by considering net present value and unit total cost as well as economical efficiencies.

![Second-stage screening results](image)

**Uncertainty Analysis**

It follows that the degree of uncertainty, and therefore the risk, is higher at the start of any EOR project, particularly in the early screening stages where reservoir characterization, EOR agent/rock/fluid interactions, and EOR field operations are not fully understood. Reservoir characterization, naturally, accounts for a large component of the overall uncertainty, followed by EOR agent/rock/fluid interactions (at the subsurface level). Reservoir imaging for EOR applications has been discussed in several papers looking not only at the reservoir heterogeneity component but also at the imaging tools required to understand the effect of the heterogeneity on the overall displacement. This reservoir imaging becomes extremely relevant when planning a pilot or any EOR field measurements. However, for the purpose of screening and this workflow, we will assume that the existing reservoir description captures the heterogeneity ranges, general ranges and not local, and that the two selected RREs are appropriate to understand the expected effect on the EOR sweep. Details on the effect heterogeneity have on pilot planning and monitoring will be discussed in a future paper.

EOR agent/rock/fluid on the other hand has a direct impact on LDE; therefore, overall recovery, and as the EOR project progresses, are the ones likely to be addressed by either field and/or laboratory measurements before determining a proper pilot or full-field implementation. It is understood that data requirements are EOR-method specific and experiments/field measures are tailored to address them individually. Furthermore, EOR agent property changes affect the viscous-gravity-capillary forces balance as well as the EOR agent requirements, making optimization under uncertainty a necessity for effectively understanding and prioritizing the influence of each parameter on the project.

Being a systematic analysis, the EOR advisor allows for evaluating the different EOR agent properties, albeit on a step-by-step fashion, to determine the properties likely to have a greater impact not only on the overall technical potential (displacement efficiency) but also on the economics (EOR agent use). A database with literature values of the most relevant EOR agent-rock properties, provided at the start of the analysis as guidance for cases where no laboratory data are available, allows the advisor to directly modify these guiding parameters and aid on the sensitivity study. **Fig. 11** shows the uncertainty effects on the displacement efficiency for a surfactant flood.
It is clear that residual oil saturation (Sor) and the shape of the desaturation curve are dominant for the optimized flooding, as one would expect. However, the differences were far different and harder to discern when no optimization was allowed on each of the runs. More importantly, these changes translated into different economical efficiencies (naturally as injection/production and surfactant concentration optimized for each run), with changes ranging from 5 to 20% on the overall incremental cost.

**Conclusion**

We have presented a data-driven EOR screening advisory tool with a flexible workflow that accommodates a different maturity of data, providing a repeatable, robust solution for clastic and dual-porosity naturally fractured reservoirs. Two sequential stages have been designed to address specific EOR needs. The first stage with limited data requirements provides a qualitative ranking of the viable EOR methods for a given field, and a second stage where a more holistic analysis is performed provides a quantitative ranking (both technical potential and economical) of the EOR options. Present and past EOR experience is combined with an evaluation of the reservoir-dominant forces, rock-quality distribution, and remaining hydrocarbon, augmented with analytical and numerical methods for displacement quantification. We demonstrated the ability of the proposed tool to select and effectively prioritize any EOR related measurements by quantifying their impact on the overall displacement. A comprehensive evaluation of past and present reservoir conditions is included within the internal logic of the system, combined with a patented workflow for estimating the local displacement efficiency on naturally fractured dual-porosity reservoirs.

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