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Development and Testing of Advanced Methods for the Screening of Enhanced-Oil-Recovery Techniques

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SUMMARY

Enhanced Oil Recovery (EOR) techniques must undergo preliminary laboratory and pilot testing before implementation to field-wide scale, and the whole evaluation process requires heavy investments. Hence forecasting EOR potential is a key decision-making element. A critical difference amongst EOR techniques resides in the oil-displacement mechanism upon which they are based. The effectiveness of these mechanisms depends on oil and reservoir properties. As such, similar EOR techniques are typically successful in fields sharing similar features. Here we implement and test a screening method aimed at estimating the optimal EOR technique for a target reservoir. Our approach relies on the information content tied to an exhaustive set of EOR field experiences. The basic screening criterion is the analogy with known reservoir settings in terms of oil and formation properties. Analogy is assessed by grouping fields into clusters: we rely on a Bayesian hierarchical clustering algorithm, whose main advantage is that the number of clusters is not set a priori but stems from data statistics. As a test bed, we perform a blind test of our screening approach by considering 2 fields operated by eni. Our predictions for analogy assessment are in agreement with the EOR techniques applied or planned in these fields.

Introduction

Enhanced Oil Recovery (EOR) techniques have become a common practice to improve the recovery factor in oil reservoirs. The wide spectrum of EOR techniques comprises three main categories, i.e., thermal methods, gas and Water Alternating Gas (WAG) injection, and chemical injection. In turn, each of these encompasses a variety of approaches. The implementation of an EOR technique on a field-wide scale is subordinated to the success of preliminary tests on laboratory and pilot scales, aimed at reducing the risk of failure of an applied project on a target field. A first metric for risk attenuation at the beginning of the evaluation process stems from the application of effective screening criteria that should enable one to assess the EOR potential and identify the most suitable technique for the target reservoir.

Each category of EOR techniques is designed to improve a specific oil displacement mechanism. As these mechanisms are strictly related to the physical properties of the oil and reservoir, screening strategies are typically based on the principle that similar EOR techniques are potentially successful on fields sharing similar oil and reservoir features. The six parameters typically regarded as representative, based on correlation analysis, are: reservoir porosity, permeability, depth and temperature and oil density and viscosity (Alvarado *et al*. 2002, Babushkina *et al*. 2013, Kamari *et al*. 2014).

An effective screening method relies on a comprehensive collection of data from previous EOR projects, as well as on acquired expertise about the mechanisms governing oil displacement in a given setting. Conventional screening methods (Taber *et al*. 1997a,b, Al Adasani and Bai, 2011) provide ranges for oil and reservoir parameters within which a given EOR technique has been proven to be successful. Figure 1 illustrates the regions of applicability of several EOR methods in the phase space of oil viscosity and reservoir depth, consistent with criteria illustrated by Taber *et al*. (1997a,b). The plot shows that gas-injection methods are effective for light-oil (i.e., small viscosity) reservoirs at large depths; heavy-oil (i.e., large viscosity) reservoirs at small depths require the application of thermal methods; chemical methods are implemented on fields with intermediate values of depth and viscosity. A strong point of conventional EOR screening approaches of this kind is their simplicity of implementation. However, they only lead to a “go/no-go” response and notably fail in providing detailed information about EOR strategies developed in similar reservoirs.
The aim of advanced screening methods (Alvarado and Manrique, 2010) is to identify fields that are analogous to the target in terms of oil and reservoir properties and to collect detailed information about prior EOR experiences at these fields. Advanced methods take advantage of data mining strategies to assess analogy between fields, including, e.g. neural networks (Surguchev and Li, 2000; Kamari *et al*., 2014) or fuzzy inference (Anikin, 2014). Recent works support the use of classification and clustering analysis as effective tools for data mining in the field of EOR screening.
The screening method developed by Alvarado *et al*. (2002) and also presented by Manrique *et al*. (2009) and Alvarado and Manrique (2010) is based on the representation of a database of EOR projects, indexed in terms of the above mentioned set of six parameters, on two-dimensional expert maps, obtained by means of multidimensional projection. These expert maps allow a joint comparison of multiple variables and a qualitative identification of clusters of fields which can be classified as analogous.
Babushkina *et al*. (2013) investigate target analogs through a k-means clustering algorithm applied on the above mentioned six-dimensional space of oil and reservoir properties. This algorithm is based on the evaluation of distances in the multidimensional parameter space and requires a preliminary definition of (*i*) a proper distance metric and (*ii*) the final number of clusters.

The screening procedure we present implements an advanced method according to which the analogy between fields is assessed by clustering analysis. Our method essentially comprises three stages, respectively aimed at: (*i*) collecting a database of EOR experiences and associated oil/reservoir properties; (*ii*) identifying clusters of analogous fields; (*iii*) analyzing each cluster in terms of the applied EOR techniques.

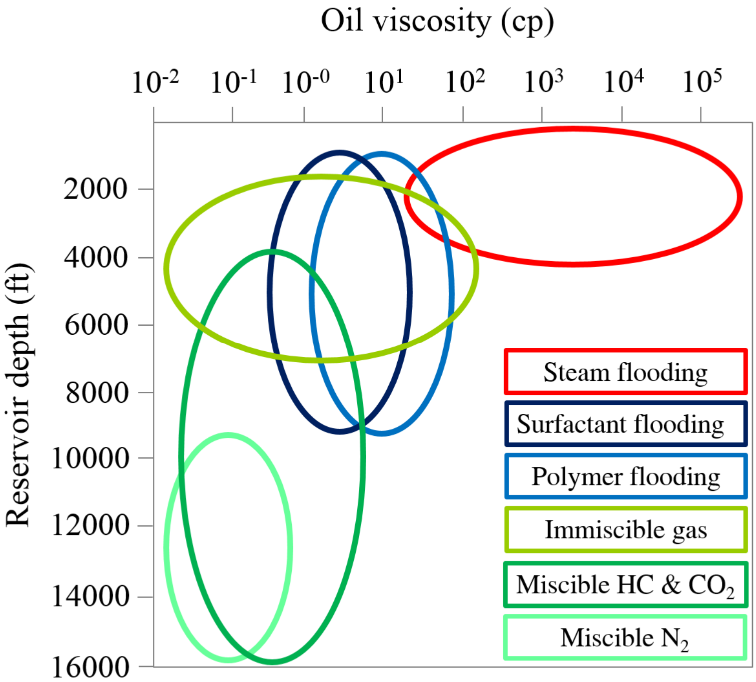

Figure 1 *Conventional screening criteria according to Taber et al. (1997a, b): ellipses represent regions of applicability of diverse EOR techniques in the phase space of reservoir depth versus oil viscosity.*

For the second stage, we take advantage of a Bayesian hierarchical algorithm, according to which cluster construction is based on a rigorous probabilistic criterion. The effectiveness of our screening procedure is investigated by performing a blind test on two fields operated by eni and already associated with EOR schemes.

Materials and methods

Our database comprises 250 EOR projects operated worldwide. The applied EOR techniques range from thermal methods (steam injection, combustion and hot water injection), through chemical injection (polymer, surfactant) to gas and WAG injection (miscible/immiscible injection of carbon dioxide, hydrocarbons, or nitrogen). Each element of the database is characterized by a set of six oil and reservoir parameters, namely reservoir porosity, ϕ, permeability, k, depth, D and temperature, T, and oil density, API, and viscosity, μ.

Data pre-processing. We start by noting that the six variables considered are characterized by remarkably different units and ranges of variability. Data standardization is then a preliminary step to be undertaken. According to Daszykowski *et al.* (2007), a robust standardization, i.e., not sensitive to outliers, can be obtained by centering data about the median and rescaling them by the median absolute deviation (MAD):

$$\xi_{RS} = \frac{\xi \text{ - median}(\xi)}{\text{MAD}(\xi)}; \qquad \text{MAD}(\xi) = 1.4826 \cdot \text{median}\left(\left|\xi - \text{median}(\xi)\right|\right) \tag{1}$$

ξ_{RS} being the robust-standardized value of a given variable ξ of the database.

Figure 2 depicts a matrix of diagrams in which (on the bottom-left side) each standardized parameter is plotted against the others. These plots show that some of the six variables considered are cross-correlated (e.g., reservoir depth versus temperature).

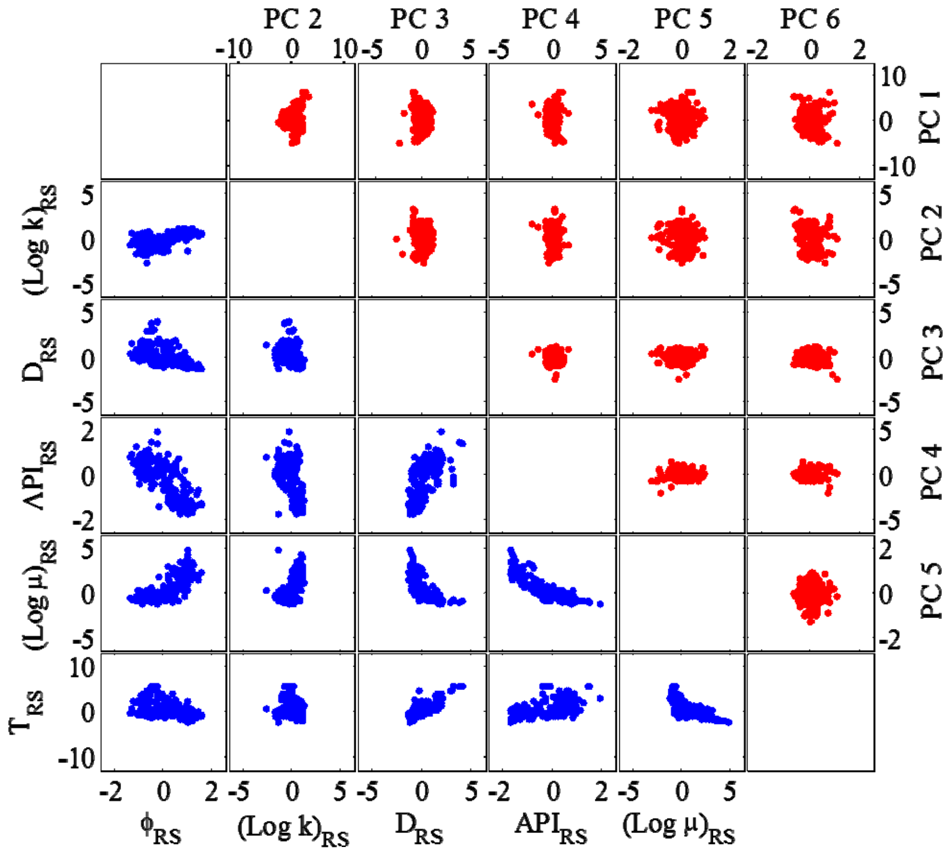

Figure 2 *Scatterplots of robust-standardized variables (lower-left side) and Principal components (upper-right side).*

The redundancy of information associated with cross-correlation can be removed by applying a Principal Component Analysis (PCA). This allows data to be mapped onto a new space of uncorrelated variables, i.e., the principal components (PC). Each PC carries a fraction of the total variability of the original system. The red scatterplots in Figure 2 (upper-right side) depict each PC against the others and demonstrate the effect of PCA in removing cross-correlation. The application of PCA results in a substantial simplification, because it enables one to reduce the problem dimensionality. As one can see from the plot in Figure 3, depicting the fraction of total variance associated with each component, 95% of the total system variability is explained solely by the first three PCs. For this reason, henceforth we can confine our analysis to the three-dimensional space of these PCs with no significant loss of information.

Clustering algorithm. Our screening procedure implements a Bayesian Hierarchical Clustering (BHC) algorithm (Heller and Ghahramani, 2005). Cluster construction in hierarchical approaches takes place iteratively, starting from an initial configuration in which each element of the dataset forms a cluster and then merging, at each step, the two most similar clusters. A basic feature characterizing the screening algorithm is the criterion adopted for the assessment of similarity between clusters. In many traditional approaches, e.g., k-means clustering, this criterion is based on the evaluation of distances in the parameter space. These approaches require therefore preliminary definitions of distance metrics, as well as of the final number of clusters. On the other hand, in BHC the notion of similarity is based on probabilistic criteria. It is assumed that: (a) the whole database is generated from a mixture associated with a given distribution model; (b) each component of the mixture is characterized by a given set of parameters; and (c) elements of the same cluster are generated from the same mixture component. Based on these assumptions, at each step BHC evaluates, for each pair of clusters, the Bayesian probability of their elements being generated by the same set of parameters and finally merges the two subsets with the highest value of this probability.

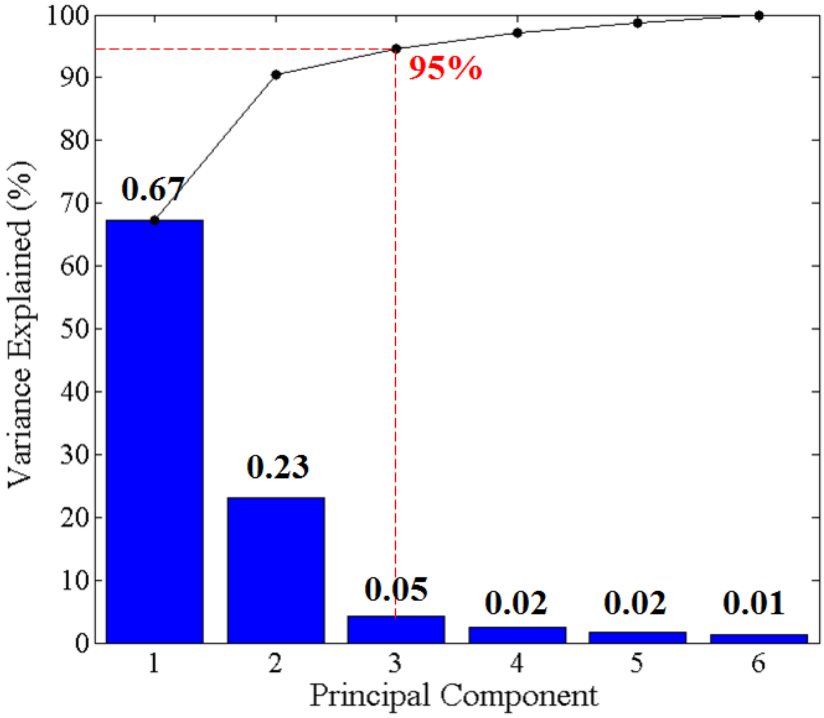

Figure 3 *Fraction of variance explained by each principal component.*

We refer to Heller and Ghahramani (2005) and Sirinukunwattana *et al*. (2013) for the detailed formulation on the computation of probabilities. As shown by these authors, the Bayesian approach is advantageous when compared to distance-based clustering algorithms (including, e.g., the k-means approach adopted by Babushkina *et al*. (2013)) because (a) it is not dependent on the choice of the distance metric; and (b) it allows inferring naturally the final number of clusters. Note that merging of clusters takes place only if the associated Bayesian probability is larger than a given threshold, which is usually set to 0.5. The merging process stops when all remaining cluster pairs are associated with a probability of being merged which is below this threshold.

Application to eni test cases

Test cases description. The screening method has been tested against two fields operated by eni (see the complete set of parameters in Table 1). These fields are at different stages of deployment where the effectiveness of specific EOR processes has been investigated.
Target 1 is a sandstone reservoir in North Africa, mineralized with light oil. Hydrocarbons are located in low net-to-gross ratio fluvial sand units. Production in the field has started from day zero with EOR techniques consisting in crestal miscible hydrocarbon gas injection. The field is also developed by means of peripheral water injection. In 2013, after a study phase, a water injector well was converted into a gas injector to increase the recovery factor, thus implementing a WAG pilot in the field.
Target 2, is a high-permeability shallow sandstone reservoir in South America, mineralized with heavy oil. Oil viscosity at reservoir condition is about 2500 cp. The reservoir is currently produced by natural depletion. Here, the aim is to apply steam injection in the future to increase the recovery factor, which is otherwise very low.

Table 1 *Oil and reservoir properties characterizing the test cases.*

	ϕ (%)	k (mD)	D (ft)	API (°)	μ (cp)	T (°F)
Target 1	14	200	8760	42	0.23	185
Target 2	29	3000	1300	8.5	2500	118

Screening results. Figure 4 depicts database elements and the two test cases in the phase space of the first two principal components (PC 1, PC 2). The application of a BHC algorithm on the data leads to identifying the eight clusters depicted in the figure and distributed over clearly distinct regions of the phase space. Data points associated with Target 1 and Target 2, also depicted in the plot, are seen to respectively belong to Cluster 2 and Cluster 1.

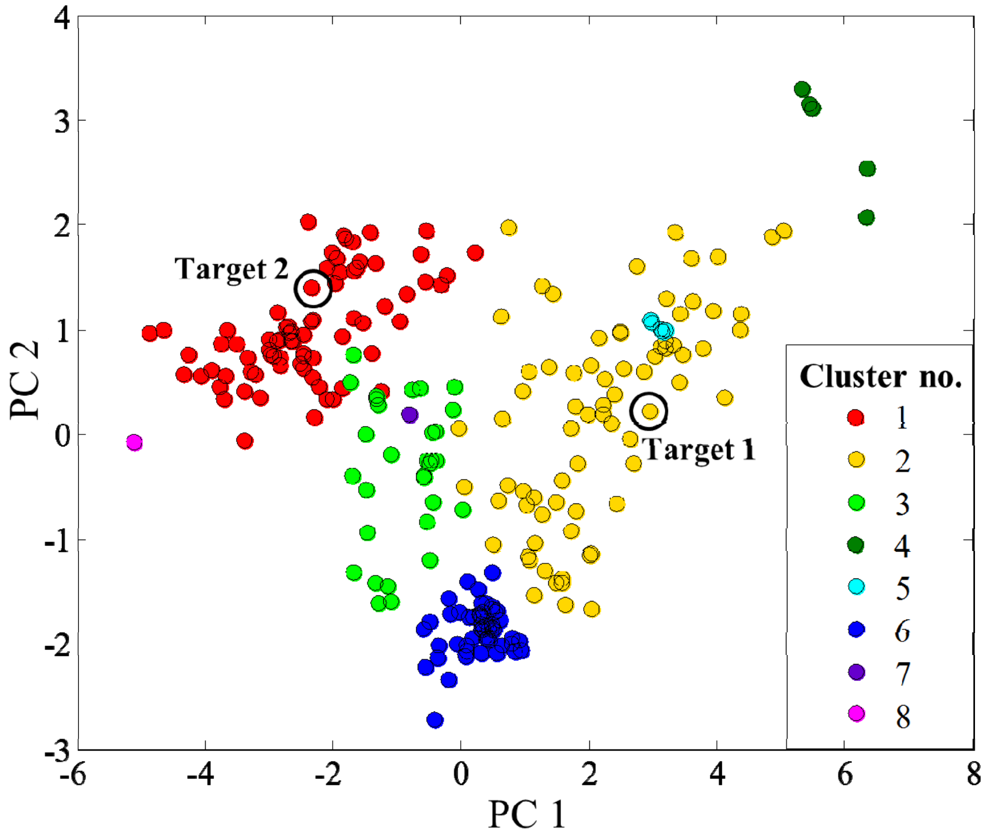

Figure 4 *Database elements and targets in the space of the first two PCs. Symbols on the color scale identify the 8 clusters obtained from the BHC algorithm.*

For the last stage of our screening procedure, we focus on the elements of these two clusters and analyse their composition in terms of applied EOR techniques.

Figure 5 depicts a scatterplot of all database elements in the space (PC 1, PC 2), EOR techniques being color-coded. This plot suggests a quite clear separation into distinct regions for the three main categories of EOR methods, i.e., thermal, chemical and gas injection. Dashed curves delimit approximately the two regions within which elements of Cluster 1 and Cluster 2 reside. Qualitative inspection of the elements of Cluster 2 reveals a clear dominance of gas injection projects within this region. This is supported quantitatively by the pie chart depicted in Figure 6a, showing the relative proportion of the diverse EOR techniques included in this cluster. About 50% of the elements of Cluster 2 is associated with (continuous or WAG) miscible injection of hydrocarbons; approximately 20% of the cluster elements is formed by CO_2 miscible injection projects. These results are consistent with the actual EOR experience at Target 1, where miscible injection of hydrocarbon gas has been performed since the early stages of production and where WAG pilots are currently under development. Hydrocarbon injection projects within this cluster are mainly concentrated in the on-shore sandstone reservoirs of the North slope region of Alaska and in the off-shore reservoirs of the North sea. CO_2 injection projects are mainly located in on-shore carbonate reservoirs of the Permian Basin, Texas.

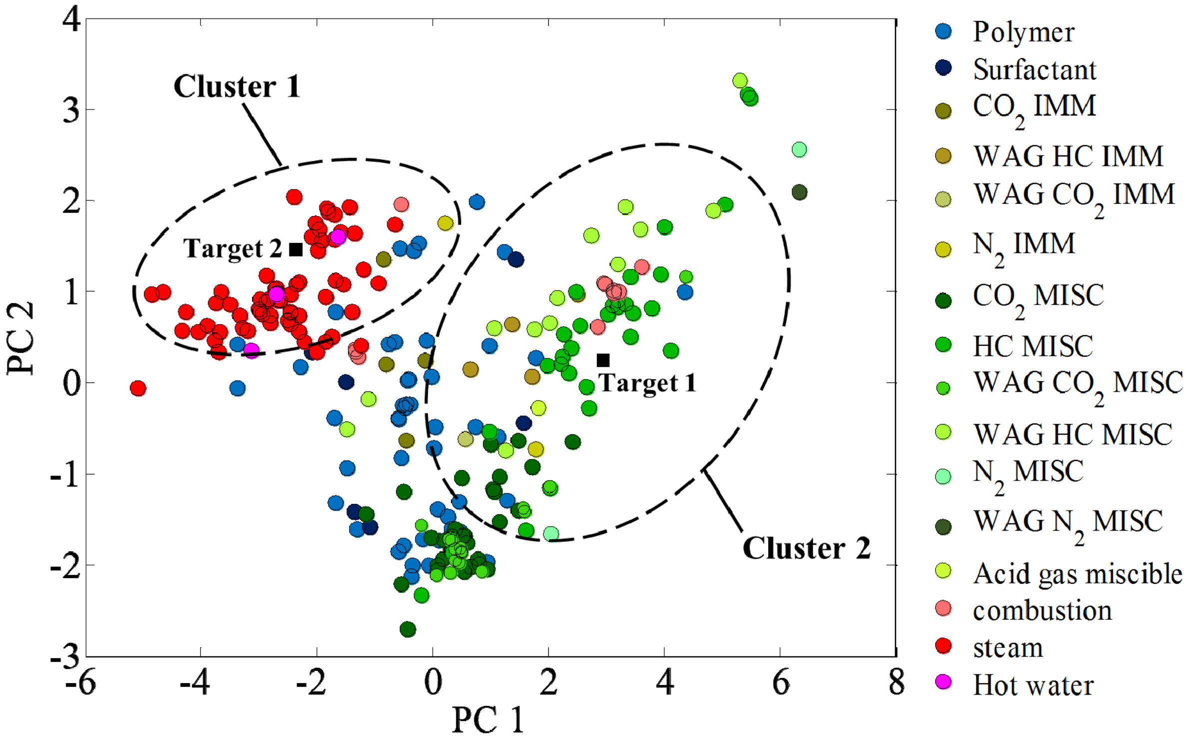

Figure 5 *Database elements and targets in the phase space of the first two PCs. Color codes identify the EOR technique associated with each element.*

In the region representing Cluster 1 in Figure 5 we can observe a net dominance of thermal projects. Figure 6b shows that more than the 80% of the elements within this cluster are associated with steam injection projects, hot water injection and combustion projects representing about 5% of the sample. Cluster 1 collects steam injection projects operated in heavy-oil reservoirs located worldwide: Alberta (Canada), San Joaquin basin in California, Venezuela and China. Also in this case, the results are found to be consistent with the EOR projects that have been planned for Target 2.

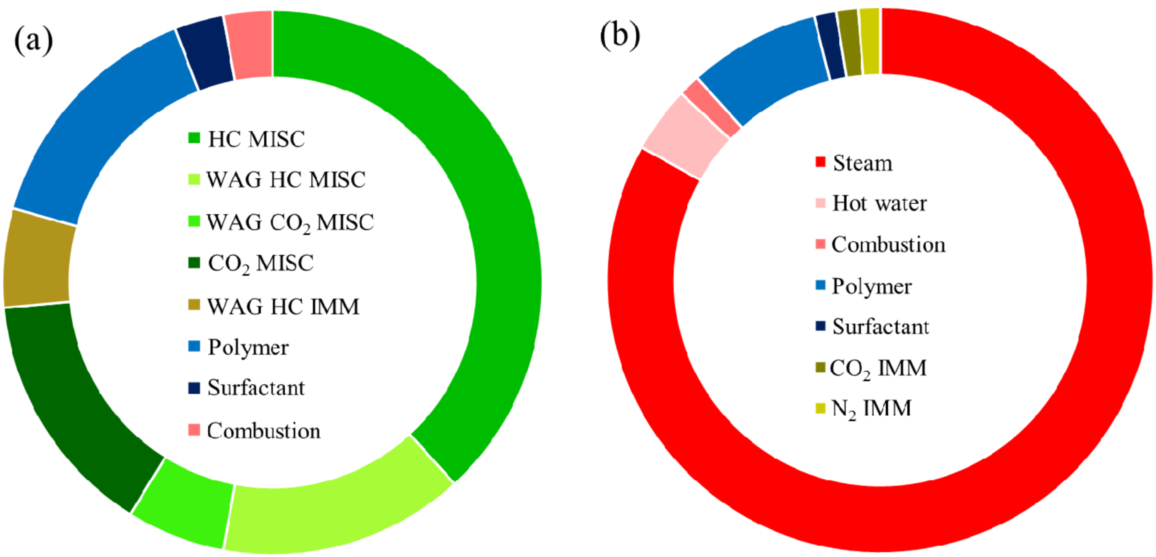

Figure 6 *Screening results: proportion of EOR techniques associated with elements in (a) Cluster 2 (i.e., Target 1 analogs) and (b) Cluster 1 (i.e., Target 2 analogs).*

Conclusions

We present, develop and test an advanced method for the screening of the best suited Enhanced Oil Recovery (EOR) technique to be applied on a given target field. Our approach relies on a comprehensive collection of previous EOR experiences performed worldwide. It relies on the identification of fields in the database that are analogous to the target, in terms of six fundamental properties/parameters: reservoir porosity, permeability, depth and temperature and oil density and viscosity.

A key element of our approach is tied to the application of a Principal Component Analysis to our data which allows significant reduction of the problem dimensionality.

Analogy is assessed through a Bayesian Hierarchical Clustering algorithm, which subdivides all data and targets into groups of similar fields on the basis of probabilistic criteria. As compared to clustering algorithms based on distance criteria, our method does not require preliminary settings about distance metrics or final number of clusters.

Screening results for a given target are obtained by studying the spectrum of EOR techniques associated with elements of the database residing in the target's cluster.

Our methodology is tested on two fields operated by eni: a light-oil and a heavy-oil bearing reservoirs. Prediction of our screening approach are consistent with the EOR strategies that have been already planned or implemented in both fields.

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