New Methodology for the Generation of the Structural and Petrophysical Conceptual Model with Limited Information*

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Abstract

Generate a plausible geological model for a green-field as well as rank reservoirs with different levels of associated uncertainty can be quite challenging. In this paper, we propose a new approach to generate predictive static models in the first stages of reservoir appraisal.

At this stage, structural, sedimentary, and petrophysical data is very limited. The workflow proposed aims to use any available information whether coming from analogues reservoirs and/or field-data to reduce uncertainty. Initially the structural uncertainty is characterized and propagated generating an ensemble of plausible scenarios based on the perturbation of predefined structures tabulated in a glossary. Subsequently the conceptual sedimentary and petrophysical model (Torrado et al., 2014) is applied for the generation of the 3D geological plausible scenarios.

The workflow has been tested on the Brugge field benchmark modified as green-field. The proposed approach respects the static and dynamic reservoir statistics using as measure OOIP and NPV respectively. In addition, the sedimentary definition of the facies is well characterized with respect to the core interpretation from laboratory.

The new workflow presented allows generating plausible geological scenarios with limited amount of information, consistently quantifying and propagating the uncertainty. Noteworthy, this workflow provides important insight on the sensitivity of the geological model to several uncertain parameters and configurations which can be the base for an optimization/risk analysis problem or to quantify the value of additional information.

Introduction

Decision making under uncertainty can be quite challenging, especially when we have to evaluate green field and the assessment has to be made relatively fast (e.g. in hours or few days). This is the case when one needs to rank a given portfolio within a limited budget and different levels of information. In this work, we propose an efficient methodology to generate an accurate geological model in the first stage of appraisal.

The novelty of the current methodology is the capability to define structural, sedimentary, and petrophysical conceptual models, based on a new integrated mathematical framework for the generation of the geological model. Noteworthy, the evaluation of the green field is carried out in the presence of geological uncertainty, therefore characterizing and propagating both uncertainty and risk.

The paper is structured as follows: initially we describe the methodology specifically focusing on the uncertainty characterization and propagation; it follows the application to a benchmark case and a summary of conclusions.

Methodology

The assessment of reserves, reservoir structure, and property distribution in a green-field can be a challenging task to overcome when limited information is available. We assume in the current methodology that no well hard data or seismic survey are available and only mean reservoir properties are accessible. At author's knowledge, with this limited information, no methodology in the literature consistently propagates uncertainty and gives a sound estimation of the geological scenarios. An internally developed reservoir analogous tool (Rodriguez et al., 2013) is used for the uncertainty quantification in absence or to complement field data. The tool supplies not only a list of analogous with a measure of its similarity but also the prediction of unknown properties and statistical distributions.

The workflow can be divided in several parts. Initially the structural uncertainty is characterized and propagated generating an ensemble of plausible scenarios based on the perturbation of structural types. In addition, structural interpretation that come from seismic and well top can be modified based on an uncertainty characterization and propagation framework. Subsequently, a novel formulation was presented in (Torrado et al., 2014) to define a conceptual sedimentary (optimum number and percentage of the facies) and petrophysical model for the generation of the 3D geological plausible scenarios. Finally, their distribution is performed automatically in order to reproduce static and dynamic reservoir measurements (e.g. OOIP, NPV, etc.).

The method is based on the formulation and solution of a multiobjective-optimization problem to compute facies and hydraulic flow units from the available data (hard data or the analog-predicted) via Monte Carlo sampling and cluster theory. The coupling between facies and hydraulic flow units is done statistically allowing multiple facies to reside on the same flow unit and minimizing the number of flow units.

Uncertainty Characterization

Throughout the workflow we can categorize the working variables twofold, uncertain and decision variables. The former are characterized by their statistics, evaluated by the analogues, with its associated similarity. The latter are defined within bounds of variations and selected by experimental design techniques in order to reduce the number of samples yet maintaining the domain of variation. In the most general case the uncertainty variables considered can be classified in structural and petrophysical. Among the firsts are reservoir area, thickness, dip angle, oil water contact (OWC), and trapping mechanism. Petrophysical properties are mean values for porosity, permeability, initial water saturation, net-to-gross, and depositional environment. The variables can of course be continuous or categorical. Depending upon the level of information considered a sampling process from its probability distribution or a predefined values based on its target value can be used.

Reservoir Structure

In reservoir characterization large emphasis should be placed on geological uncertainty and risk. The danger of working with a single deterministic model is evident in the context of decision making under uncertainty. Although typically large uncertainties are associated with the reservoir structure, the reservoir geometry is usually fixed to a single interpretation and the reservoir characterization is often based in a set of sedimentary and petrophysical realizations. Limited automation of current meshing tools and difficulties of integration in decision workflow is often the cause of lack of propagation in structural uncertainty. Different approaches and modeling techniques exist to generate multiple realizations of reservoir structures for various uncertainties (Abrahamsen 1993 and Holden et al., 2003) a nice review and application in the context of the assisted history-matching can be found in (Seiler et al., 2010). In the following we propose two methodologies in order of increasing available information to characterize the structural uncertainty here named as ‘glossary’ and ‘grid deformation’.

When the only structural information comes from analogues or expert sentiment, the structural uncertainty workflow is initially associated to reservoir structural types. Each type is tabulated in a glossary (i.e. anticlinal, pinch-out …) and defined by a set of mathematical functions whose coefficients can be defined consistently with the statistics above mentioned. In other words, defined a set of structural uncertain variables and a set of structural decision variables a structural realization can be consistently defined to match them. Initially a normalized function of the top horizon is generated to match the given reservoir dip angle. Subsequently the computed function is de-normalized to match the reservoir area above the OWC. A Newton-Rapson solver allows the accuracy of the results within a predefined level of tolerance (Figure 1). The reservoir thickness is considered constant. This methodology does not allow to automatically include faults which have to be specified manually if any.

On the other hand, if enough information is available and the structural model is available as iso-level map or computational mesh based on well tops and/or seismic interpretation, the current workflow is capable from a deterministic model to generate a set of structural realizations still respecting the hard data. This methodology is based on the elastic grid deformation (Thore et al., 2008 and Seiler et al., 2010) applied to all the reservoir horizons. Hence, a stochastic simulation of the reservoir deformation matrix is computed and applied to the original mesh. For clarity we consider here the case of only well hard data available and the same deformation matrix applied to all horizons. Initially a semi-variogram is fitted to the well top data. This is applied using a kriging interpolation to generate the predicted horizon and its variance. A sequential Gaussian simulation is then used to generate stochastic realizations based on the computed variance this time applied to the deformation (original –predicted depth). By definition the deformation at well location is zero if the semi-variogram nugget is zero. A smoothing step of the deformation matrix is used to give robustness to the entire process and to avoid excessively skewed cells that will penalize the convergence of the dynamic simulation. The deformation matrix computed and applied to all horizons. By superposition principle the layers will have a deformation resulting by the composite deformation of neighbor horizons yet maintaining a cell aspect ratio to ensure convergence of the dynamic simulation. A mesh quality check should also be performed considered that for large deformation a grid deformation process may fail and a new meshed grid should be used instead. The advantage of working with a deformation matrix instead of horizon coordinates is the ability to preserve discontinuity (i.e. faults) inherently in the workflow.

Conceptual Sedimentary and Petrophysical Modeling

The lack of core or well data in the first stages of the prospect and/or the difficulties in analyzing these data unbiasedly has motivated the development of an in-house algorithm to estimate facies (number and percentage) as well as the petrophysical properties statistical distribution conditioned on facies, (Torrado et al., 2014).

The method is based on the formulation and solution of a multiobjective-optimization problem to compute facies and hydraulic flow units from the available data (hard data or the analog-predicted) via Monte Carlo sampling and cluster theory. The coupling between facies and hydraulic flow units is done statistically allowing multiple facies to reside on the same flow unit and minimizing the number of flow units.

The algorithm developed returns the porosity/permeability correlation conditioned on facies and its standard deviation about the conditional mean. To compute initial water saturation and net-to-gross a correlation between oil saturation and rock quality index as well as net-to-gross and porosity respectively is inferred from the optimized facies solution which allows the complete estimation of the petrophysical correlation necessary for the conceptual model generation (Figure 2).

Property Distribution

The distribution of properties is the last step to complete the generation of the petrophysical realizations. The characterization of the spatial variability should make the most of all available information related to the sedimentary and depositional environment in order to generate a geological plausible conceptual model.

The current methodology makes use of two-point and multi-point geostatistics to distribute facies and petrophysical properties. The strength of this step is the ability to manage a high number of uncertain variables to generate statistically independent realizations spanning the entire uncertainty domain with limited number of geological realizations. We make use of experimental design techniques and multidimensional scaling analysis in order to limit the number of output realization yet keeping the same level of uncertainty propagated (Caers 2012 and Torrado et al., 2013).

Results

The methodology presented in this paper has been applied to the Brugge SPE benchmark (Peters et al., 2009). The benchmark has been treated in the present work as a green-field. The parameters input to the reservoir analogues tool have been extracted from the ensemble average of Brugge's realizations and are listed in Table 1. The public realizations are priors models not history matched and with no structural uncertainty.

Hence, a fair comparison between the generated realizations and the literature ones are consistent only if the input data to the workflow are directly extracted from the latters.

Additional parameters and probabilistic distribution not included among the inputs have been estimated using data mining algorithms to help the construction of the conceptual model.

Brugge has been taken in the present work as a reservoir in the first stage of a green field where only the data distribution presented in Table 1 is known. The workflow described in this paper has been applied and a set of 104 structural and petrophysical realizations have been obtained for Brugge 'Conceptual Model' respectively.

The results of petrophysical and sedimentary model described above were compared against the sedimentary facies interpretation of the field-data in (Peters et al., 2009). Figure 3 shows that the predictions are aligned with the expert interpretation in number and probability distribution of petrophysical properties as was presented elsewhere (Torrado et al., 2014).

The realizations generated by the geological conceptual model has been validated initially from a static perspective by comparing the statistics of the Original-Oil-in-Place (OOIP) with respect to Brugges' 104 Full-Field Model (FFM) ones. As can be seen in Figure 4 the predicted statistic of OOIP generated from the CM realizations compares well with the FFM. We can notice 3% over-prediction in the mean yet completely enveloping the FFM results.

The Net-Present-Value (NPV) value has been selected as dynamic measure to compare the dynamic response of the realizations. It is assuming the same economical setting as reported in the literature (Peters et al., 2009). The NPV value is computed locating a five-spot pattern under constant water injection in order to cover the entire oil zone. The results presented in Figure 5 as NPV quantiles at the end of field production show a shift with respect to FFM but a yet reasonable estimation of the P50, yielding to an enlarge boundaries of P10 and P90 percentiles. This effect is clearly expected due to the uncertainty associated with CM is higher.

The deviation from the FFM results are here attributed to the selection of the structural type defined as anticlinal instead of anticlinal half-dome and the presence of the fault with no transmissibility. This choice was determined by the need to exploit the lowest level of information therefore the worst case scenario in order to fairly apply the methodology. Despite this small deviate in the solution we consider this a successful application of the workflow. Results in absence of structural uncertainty have been presented elsewhere (Torrado et al., 2014).

Conclusions

The current paper presents a new methodology to generate plausible conceptual geological models when limited information is available. New techniques have been proposed for the generation of the structure, petrophysical, and sedimentary model and their spatial propagation in 3D, quantifying and propagating the uncertainty inherent to the reservoir. Particular emphasis has been given to the structural uncertainty where the glossary and the grid-deformation methods have been proposed and tested. This methodology was tested on Brugge benchmark case, showing good predictive capabilities for petrophysical properties (optimum number and percentage of facies), original oil in place, and dynamic reservoir response (NPV). The approach of structural deformation matrix here introduced will be further extended adding the conditioning on a seismic interpretation and the coupling to an automatic meshing algorithm capable to include large deformation to the original grid yet maintaining a good quality of discretization.

Acknowledgments

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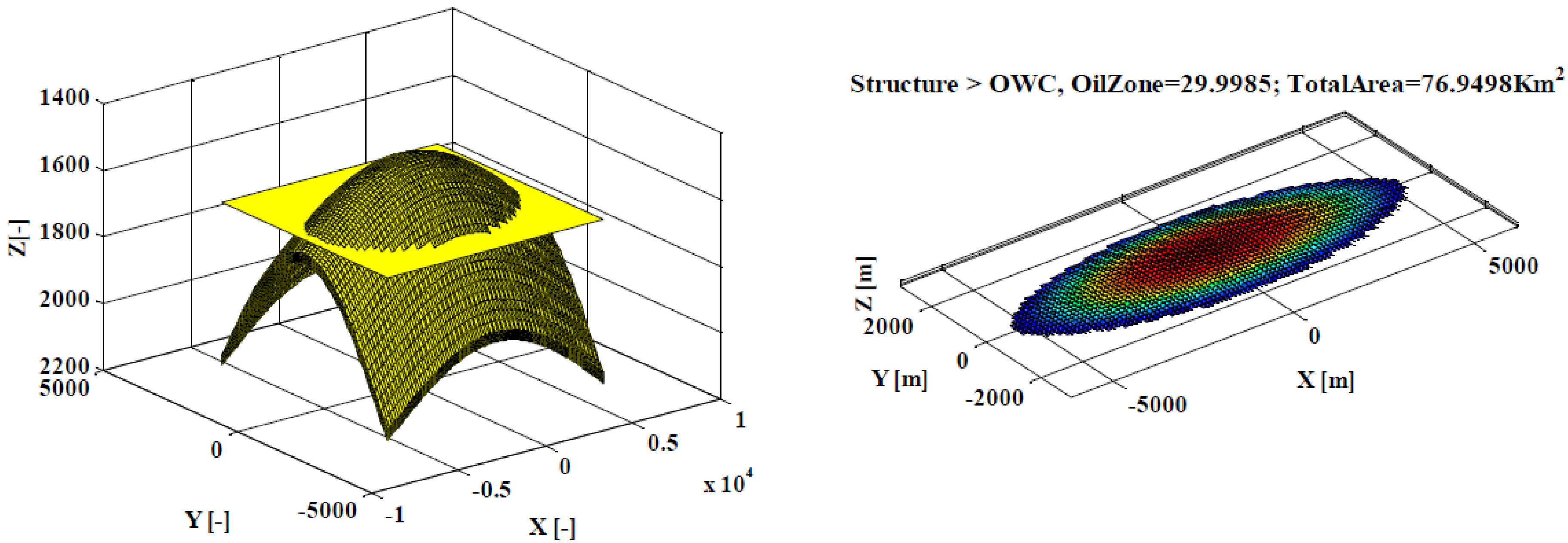

Figure 1. Anticlinal normalized reservoir structure and corresponding OWC (left). Structure de-normalization to match area and dip angle constrains (right).

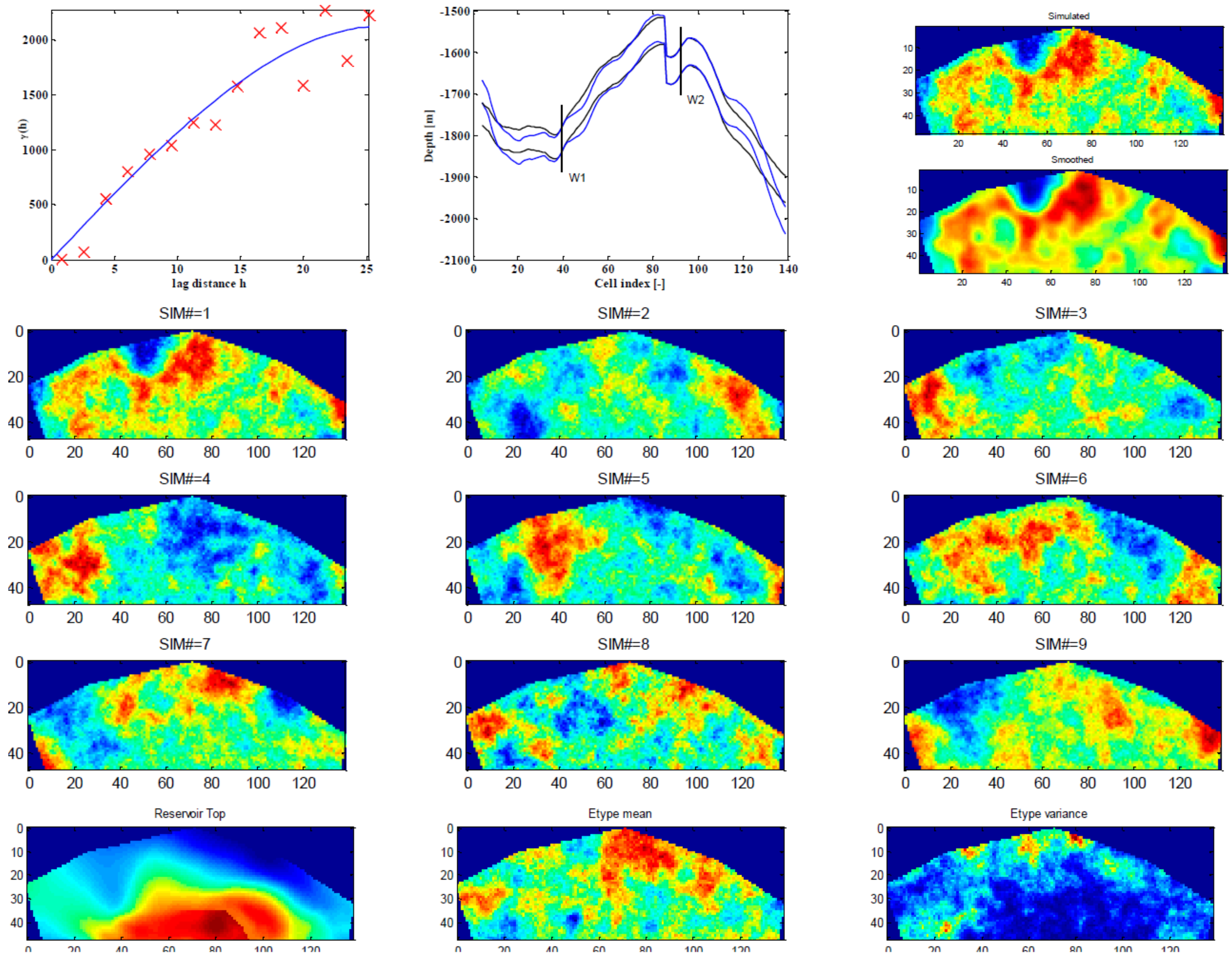

Figure 2. Elastic grid deformation methodology: Semi-variogram well tops (top left). Resulting grid deformation section (top center). Horizon perpendicular deformation matrix and smoothed realization (top right). 9 Sampled deformation simulations (middle). Reservoir top horizon (bottom left). Mean deformation (bottom center). Deformation variance (bottom right).

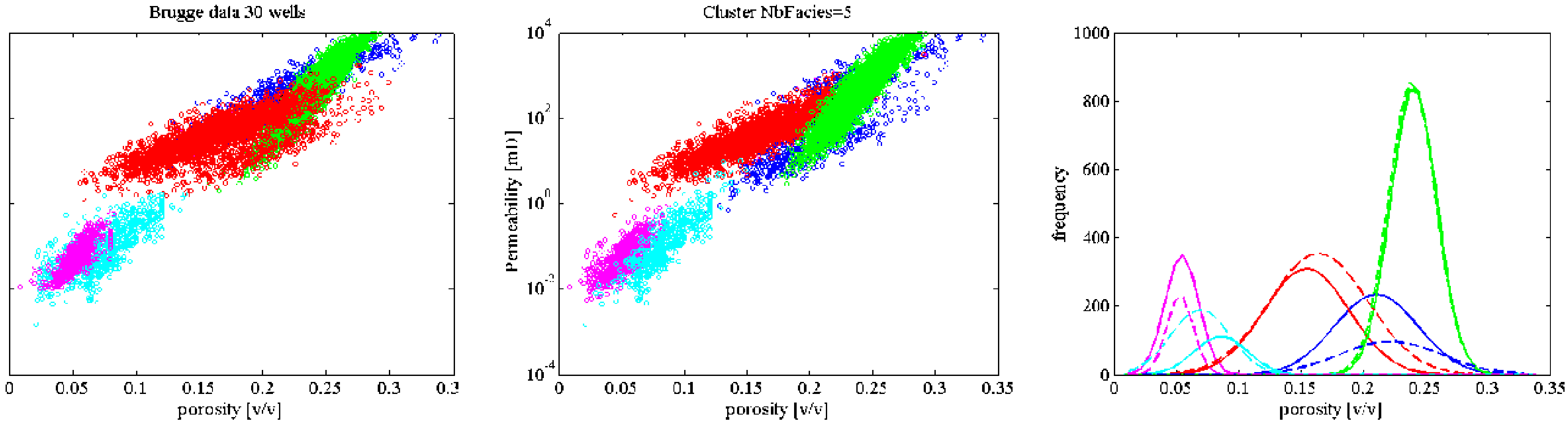

Figure 3. Facies prediction from core data courtesy of (Torrado et al., 2014).

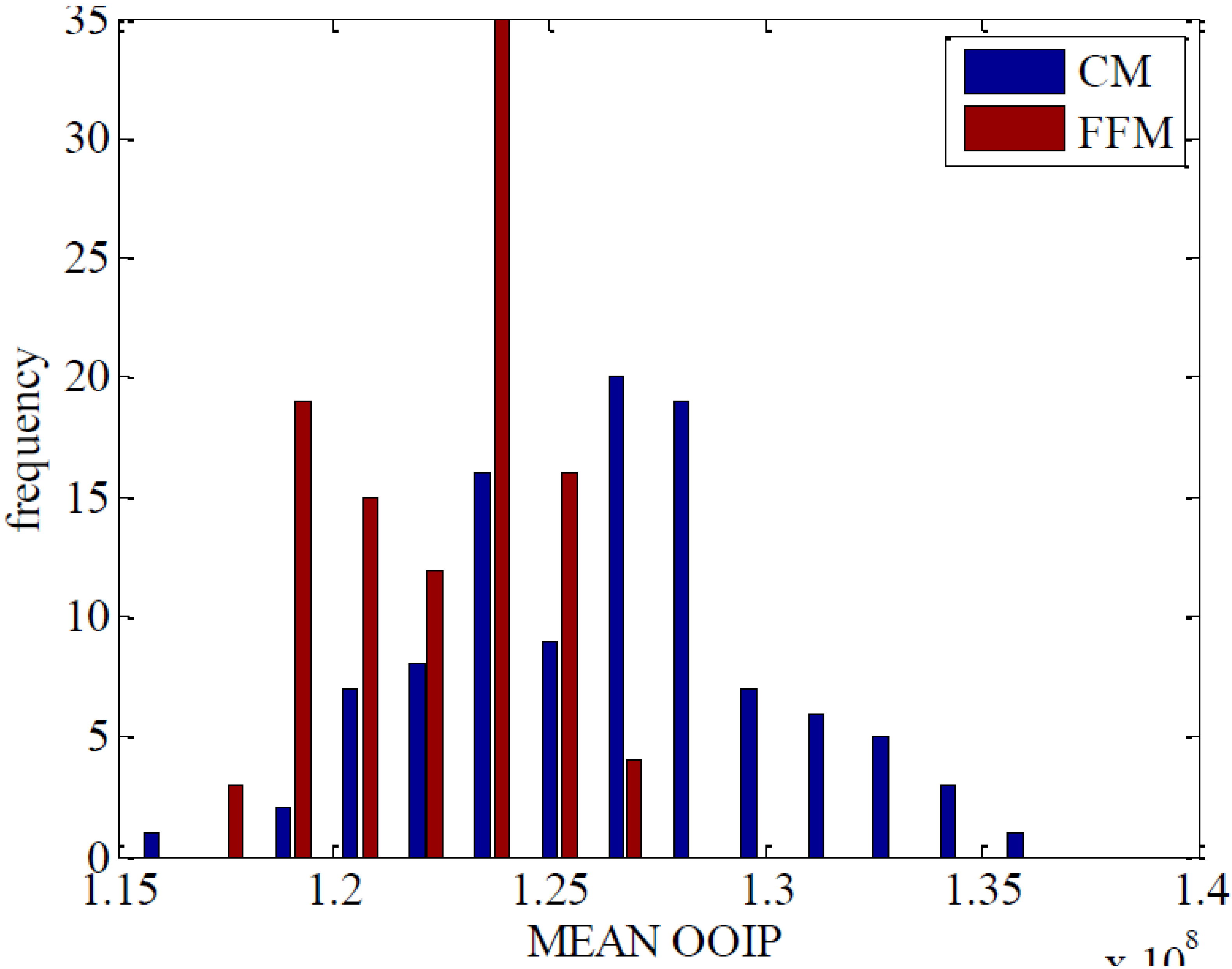

Figure 4. Original-Oil-In-Place current methodology (CM) and Brugges' realizations (FFM). Average $OOIP_{FFM}$ = 122.42 10^6 [m^3], Average $OOIP_{CM}$ = 126.5 10^6 [m^3].

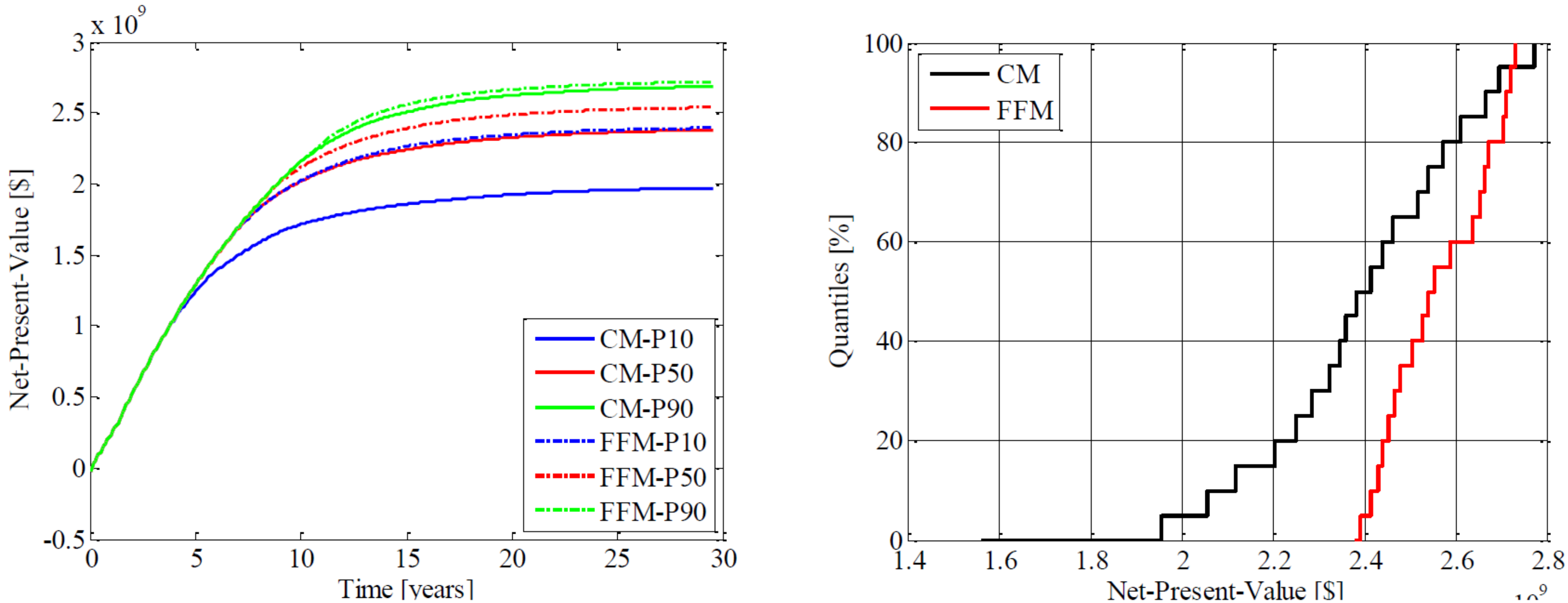

Figure 5. Net-Present-Value for CM and FFM. Evolution in time of NPV quantiles P10, P50, P90 (left). NPV quantiles at the end of field exploitation (right).

Known Parameters	Value	Known Parameters	Value
Sedimentary System	Fluvial	Trap System	Anticlinal
Mean Porosity [%]	18.6	Top Depth [m]	1511.6
Mean Water Saturation [%]	36.6	Dip Angle [º]	12
Mean NTG [-]	0.9	Area [km2]	30
Mean Permeability [mD]	315.2	Thickness [m]	45

Table 1. Sedimentary and Structural input parameters.