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Key Factors Affecting 3D Reservoir Interpretation and Modelling Outcomes: Industry Perspectives

V. Singh[1*], I. Yemez[1] and J. Sotomayor[1]

[1]Repsol, Mendez Alvaro 44, Campus Azul (IIIrd Floor), 28045 Madrid, Spain.

Authors' contributions

This work was carried out in collaboration between all authors. All authors read and approved the final manuscript.

Review Article

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ABSTRACT

To properly characterizing and modelling a hydrocarbon bearing reservoir is not an easy task because the reservoir properties vary spatially due to reservoir heterogeneities which occur at all scales, from pore scale to major reservoir units. The level of reservoir complexities under study determines the quantity and quality of data requirements for 3D reservoir modelling activity. An adequate understanding of the limitations imposed by the data, associated uncertainty, or the underlying geostatistical algorithms or approaches and their input requirements for the 3D reservoir models are absolutely necessary to obtain reasonable production forecasts. Generally, industry look-backs continue to show the difficulty of achieving a production forecast within an uncertainty band (P90 and P10) for both "Greenfield" projects with limited data and "Brownfield" projects with abundant data. Some of the identified key factors affecting production forecasts are: sparse and non-representative data, biased estimates of Original Hydrocarbon In-Place, non-representative inputs distribution in the reservoir models, inadequate static and dynamic models, poor use of seismic data, use of improper analogs, non-unique history matching calibration processes for brownfields and inappropriate use of uncertainty workflows and tools. This paper briefly discusses some of these factors which affect 3D reservoir interpretation and modelling outcomes for the conventional reservoirs, to provide better understanding, propose effective and practical solutions to improve production forecasts based on lessons learned from 3D reservoir modelling studies, authors and industry experiences. In recent years, the industry has developed and used some high-level fit-for-

**Corresponding author: E-mail: vsingh@repsol.com, 86singhV@gmail.com;*

purpose workflows with a closed loop between 3D static and dynamic reservoir modelling under uncertainty with use of appropriate geo-statistical techniques and history look-backs approach which assist capturing the uncertainties in production forecasts and improving the project risks assessment. The evolution of closed loop modelling process will continue as new techniques and technologies are developed and implemented, enhancing our ability to capture the physical realities of the real subsurface world, generate better production forecasts to reduce the risk associated with field developments.

Keywords: Reservoir characterization; modelling, facies; petrophysical parameters; simulation; production forecasts; uncertainty; risks.

ACRONYMS AND ABBREVIATIONS

2D/3D SEM – 2D-3D Scanning Electron Microscopy; 3D – Three Dimension; API – American Petroleum Institute; ASHM – Assist or Semi Automatic History matching; Bbls – Barrels; CPU – Central Processing Unit; E&P – Exploration and Production; EOR – Enhanced Oil Recovery; FIB –Focused Ion Beam; GOR – Gas Oil Ratio; HM – History Matching; LPM – Lithotype Proportion Matirx; m – meter; MBO – Millions Barrels of Oil; Micro-CT – MicroComputed Tomography; MPS – Multiple Points Simulation; N/G – Net to Gross Ratio; OHIP – Original-Hydrocarbon-In-Place; OOIP – Original-Oil-In-Place; OTC – Offshore Technical Conference; OWC - Oil Water Contact; P90, P50 and P10 – 90%, 50% and 10% probabilities; P_c *– Capillary Pressure; PGS – Pluri-Gaussian Simulation; PVT – Pressure Volume Temperature; QA-QC – Quality Assurance Quality Control; SGS – Sequential Gaussian Simulation; SIS – Sequential Indicator Simulation; TI – Training Images; TSGS – Truncated Sequential Gaussian Simulation; TVDSS – true Vertical Depth Sub Sea;* V_p *- Compressional (P) Wave Velocity;* V_s *– Shear (S) Wave Velocity; X-Ray CT – X-Ray Computed Tomography.*

1. INTRODUCTION

Finding and developing oil and gas assets has always been a risky business. The industry has a history of technological advances that have helped to reduce the risk, even as reservoirs and the way they are produced have grown in complexity. However, risk has not been fully reduced due to inherent uncertainties in the workflows used to generate production forecasts of the oil and gas fields [1-4]. According to Rose [5], in the last 20 years of the 20th century, E&P companies delivered only about half of the predicted reserves. Merrow [6] reported in his study that since 2003, the rate of success for E&P megaprojects (>1 Billion US$) has declined from 50% to 22%. The main reason for industry underperformance is attributed to use of evaluation methods that do not account for the “full uncertainty”. More importantly, a disappointing 64% of these projects experienced serious and enduring production attainment problems in the first 2 years after first oil or gas.

3D reservoir models are constructed for various purposes in the E&P business and support value-based decisions including: (1) development planning, estimation of reserves, commerciality decisions, acquisitions or farm-in opportunities, re-development of old fields and (2) asset management throughout the production period, execution and monitoring, water flood / EOR planning, production cessation/ abandonment. The reservoir modelling process is cyclic and never really ends (new data, new technology or new analogs). Industry experience clearly shows that production forecasts obtained from these 3D reservoir models are often highly uncertain for "Greenfield" as well as "Brownfield" projects [7,8].

There are highly visible efforts in the industry to improve development planning and production forecast accuracy which are mainly driven by the E&P business needs, exponential growth in advances of computing since the early 90's and advances in software (Fig. 1a). Today, existing computers can easily deliver teraflops (10^{12}) to petaflops (10^{15}). Improved parallel networking algorithms have significantly decreased the Central Processing Unit (CPU) run time by building large computers of distributed memory of up to 500 CPU machines [9]. These rapid developments of CPU and technologies in computing advances have lead to:

- The mathematical transformation of 10's to100's of terabytes of seismic data recorded in a modern 3D seismic survey into high resolution subsurface images that geoscientists can interpret with higher confidence [10, 11].
- Convert 3D seismic data into rock properties (Lithology, VP, VS, density, porosity, permeability, saturation, etc.) realizations through full wavefield and general inversion which require intense computing resources [12, 13].
- An exponential increase in cell counts since the 1990's (from few thousands cells in 1990's to billions of cells in 2012) in 3D reservoir models (Fig. 1b). This is associated with a significant decrease in the 3D reservoir model cell size from 300 - 600m in 1990's to 5 - 10m in 2012 as can be seen in Fig. 1c [14]. These 3D reservoir models have allowed better capture of geological heterogeneities.
- The reduced CPU run time for dynamic simulation which has significantly reduced or eliminated up-scaling of large size 3D static reservoir models (Fig. 1d). Higher numerical solution accuracy and flexibility to handle fully integrated Giga-Cell 3D reservoir models, in-turn, has improved production forecasts predictability under uncertainty [15-17].

However, there are still several major issues in 3D reservoir modelling that need to be addressed.

Some of these issues, related to the conventional clastic/carbonate reservoirs without fractures, are discussed along with effective and practical solutions proposed based on lessons learned from 3D reservoir modelling studies, authors' and industry experiences. The presence of fractures in different reservoirs further adds the level of complexities on these issues which are not considered in this paper. It is emphasized that if data QC, geological rules, mapping principles and geostatistics are not handled properly, the resulting model will be less appropriate, regardless of the sophistication of the software and algorithms deployed. Therefore, in-depth understanding and incorporation of these aspects and use of subject experts' knowledge from different disciplines in the 3D integrated reservoir modelling process is critical and will continue to improve reservoir modelling outcomes as new state-of-the-art techniques and technologies are developed and implemented. This in turn will enhance our ability to capture the physical realities of the real subsurface reservoirs and reduce the risk associated with field developments.

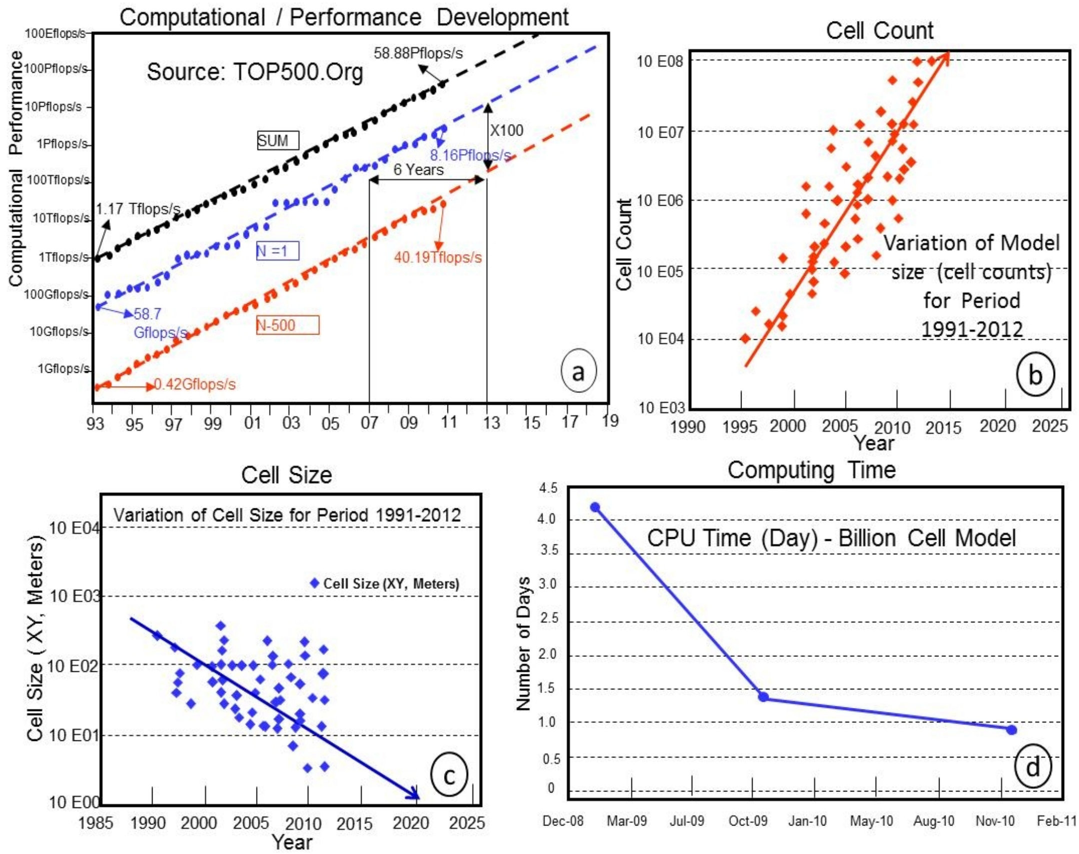

Fig. 1. (a)Increase in computation since 1993 based on top 500 computers (b) Increase in cell counts over the period 1991-2012) (Modified after Dogru, 2011) (c) Variation of geological model size (decrease in cell size over the period 1991-2012) and (d) Reduction in computing time for a giga-cell model (Source: Dogru, 2011)

2. FACTORS CONTRIBUTING TO PRODUCTION FORECAST UNCERTAINTY

How can one interpret reservoir behaviours and trust production forecast capabilities of a 3D reservoir model to be used for critical investment and decisions? To properly answer this question, one must characterize and quantify all of the main uncertainties e.g. raw data measurements, processing and interpretation, structure, stratigraphy, facies and petrophysical modelling, transmissibility calculations and flow simulation inherent in the 3D static and dynamic models. Techniques are used by calibrating models to available measurement data and by propagating model inputs uncertainties to model outputs with highest expected accuracy. Interpolating the models prediction is meant to improve the confidence of a given simulation that has some predictive capability. The predictability and confidence of these models are validated using some of the wells not used in the modelling or with of new wells drilled to prove the modelling outcomes. Some of the identified possible causes for production forecast uncertainty are:

- Lack of tools that properly integrate all the data. Improper use of 3D reservoir modelling and uncertainty workflows. Geostatistics failed to provide a solution for modelling many complex reservoirs and is very limited on the use of multiple seismic attributes. Modelling porosity with impedance as a soft constraint does not work in many complex geologic settings because porosity is controlled by many other factors some of which are not represented by the impedance. Poor porosity models affect the OHIP, 3D static and dynamic models. Usually, there is an incomplete evaluation of reservoir uncertainties and their impact on production forecasts is not fully analyzed.

- Original or remaining Hydrocarbon In-Place generally too high due to:

  - Sparse data.
  - Non-representative data: Biased to better reservoir quality.
  - Inadequate or improperly analogs use.

- Geological (static) models are inadequate due to:

  - Data limitation, quantity and quality.
  - Failure to adequately model uncertainty.
  - Optimistic N/G ratio distribution (reservoir versus non-reservoir).
  - Inconsistent facies and reservoir properties distribution.
  - Unidentified permeability contrasts-baffles/barriers, thief zones (reservoir complexities not captured).

- Simulation (dynamic) models are inadequate due to:

  - Data limitation, quantity and quality.
  - Poor link between static and dynamic models.
  - Poor and simplified up-scaling from fine to coarse grid used for history matching & production forecasts (grid size). This is particularly critical when secondary and tertiary recovery mechanisms (e.g. water flooding and gas injection) are implemented.
  - Simplistic History matching procedures.

As part of the Quality Assurance-Quality Control (QA-QC) process within our company to improve the technical quality of the portfolio of projects and reduce investment risk, a total of around fifty QA-QC events were carried out over a 5 years period. Around 47% of the findings (recommendations for improvement) were related to 3D static and dynamic reservoir modelling improvement opportunities (Fig. 2). These identified issues during the QA-QC process in different projects were very similar to those identified by the industry globally [7].

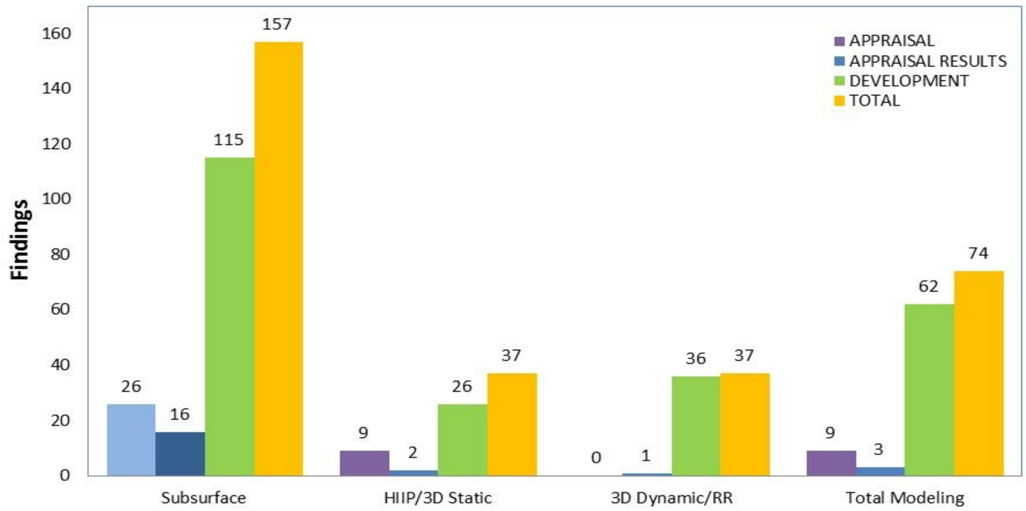

Fig. 2. Findings from QA-QC events in 3D reservoir modeling

2.1 Issues Related to Integrated 3D Reservoir Modelling Workflows

An efficient data management system for the vast amount of input data and software integration is a critical component of the 3D reservoir modelling process. In a typical high level reservoir modelling and forecasting workflow (fast-track) used in the industry, the static and dynamic models are built, honouring the limited available well data and may be a single seismic attribute in the best case scenario, with no consideration of uncertainty. In this process, typically, geological insights and seismic data are first interpreted and the results are combined with petrophysical interpretation and used to construct a static model. During this process, most often, geostatistical techniques are misused due to lack of their good understanding, proper application and lack of time to generate multiple realizations. As a result, a single static model is then exported into the dynamic domain where a single forecast is generated without any feedback between static and dynamic models. The data interpretation involved in this process requires multiple assumptions to be made and the feedback loops used to verify them are often very limited or non-existent. Another shortcoming of the typical workflow is little or no focus on delivering uncertainty at each step of the process related to dynamic outcomes. Typically, each discipline tries to pass a deterministic answer to the next one. Uncertainty is usually investigated at each step to explore volumetric ranges and obtain history matches without any integrated QC of the adjusted ranges. This sequential modelling often makes it difficult to investigate the impact of static model uncertainty in the dynamic realm, because the static parameters variability and its impact have effectively been predetermined. Interdependencies cannot be properly identified and history matches often lead to manipulation of dynamic parameters or arbitrary modifications of permeabilities, without consistent changes to the precursor properties (such as porosity, facies, saturation) from which they were derived.

To address these limitations of conventional modelling workflows, in recent years, the industry has started using a closed loop modelling workflow in which the impact of all modelling parameters and their uncertainties on a particular decision outcome are being represented, i.e., the so called “high level closed-loop modelling and forecasting workflow” keeping in view the input data, modelling objectives and project timelines. In this workflow, all the model components are simultaneously tested against an outcome, thereby quantifying the potential impact on uncertainty on development decisions. There are several papers and text books that discuss the uncertainty assessment using different methodologies: (1) experimental design [18-24]; (2) Monte Carlo simulation [1,25] and; (3) stochastic approach [26-28].

The most significant aspect of the experimental design workflow is that a probabilistic forecast is made which respects uncertainty and allows identification of the critical parameters that may have significant impact on the hydrocarbon in-place, recoverable resources and production forecasts. The workflow allows closer and faster collaboration between the different disciplines involved in the reservoir study. The feedback coming from the dynamic modelling and history match can be incorporated into the structure for the 3D static model and its impact on the 3D dynamic model. The implementation of this closed-loop with feedback between static and dynamic models is iterative in nature. It has proven to be very useful in integrating the expertise of various team members to synchronize a team effort to a common goal. The iteration within model development is motivated by the evolution of simple models to more advanced models when additional data is collected during field development and as more information and understanding of a particular model is developed. A schematic closed-loop modeling workflow used in the industry is shown Fig. 3 which includes uncertainty assessment steps as well as experimental design based workflow steps to generate a set of probabilistic (e.g. P90, P50 and P10) static and dynamic models used to generate probabilistic production forecasts.

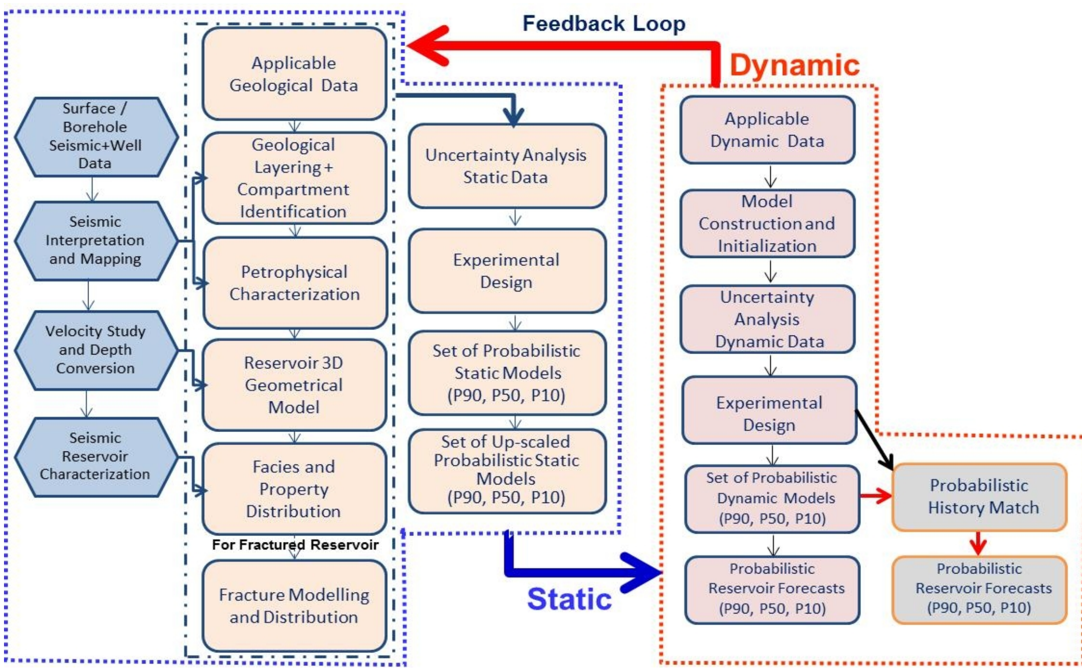

Fig. 3. Currently used probabilistic closed-loop 3D reservoir modelling workflow

For exploration and production, Rose [29] has illustrated the several advantages of probabilistic methodology over deterministic methods which include:

- Accuracy of estimates can be measured, so estimator can be accountable.
- Use of statistical tools improves the estimates.
- Predrill reality checks can detect errors before drilling.
- Reserves/resources estimation is faster, more efficient and avoids false precision.
- Realistic communication of uncertainty to decision makers and investors is facilitated.
- Results are immediately usable in modern portfolio measurement.

However, there are several shortcomings in the normally used tools (e.g. stochastic, probabilistic, Monte Carlo simulation results) for uncertainty and impact assessments. Some of the important quotes for these statistical tools by the industry experts [30] are as follows:

- “The crucial weakness of the stochastic approach is in the inability to assign probabilities with any degree of certainty”.
- “Monte Carlo simulation results are only as good as the subjective input assumptions of the user”.
- “Assigning probabilities to the decision tree branches requires technical expertise as well as considerable domain knowledge, and specialists from many disciplines have to be called in for subjective judgement about critical parameters”.
- “Apparent capture of uncertainty through probability distributions encourages intellectual laziness”.
- “Simulation lacks the ability to incorporate a wide range of knowledge - key to decision making - from analog fields and studies”.
- “Real reservoirs are so complex that the available elegant mathematical tools used to quantify uncertainty and risks are only of limited use”.

In many ways these shortcomings are still valid. Therefore, understanding the basic assumptions, input requirements for the specific statistical technique used in the 3D reservoir modelling process, use of expert knowledge from different disciplines with their skills, selection of appropriate workflows and quality checking of the data as well as the results at every step of the process are critical to achieve the defined objectives of 3D reservoir modelling.

2.2 Impact of Limited Data (Quantity and Quality) on Ohip Estimation in Greenfields (Appraisal and Early Development Phases)

Often during exploration and appraisal stages of different projects, relatively safe wells are drilled with the focus to obtain data that will confirm the presence of significant amount of oil and gas. The data obtained from these wells is used along with analog data/information to support the technical evaluation (OHIP, recoverable resources/reserves, well productivity, production forecasts, etc.) and further E&P activities. Authors experience on different E&P projects continue to show the difficulty of achieving hydrocarbon-in-place estimates within the evaluated uncertainty band (P90 and P10). This is usually due to the uncertainties of different input parameters and their ranges which are often not estimated properly. This is mainly due to two problems: (1) Need of more data to be acquired as the project moves from one stage to the next during the early asset life and (2) suboptimal or limited use of existing data/information.

There are very limited examples available in public domain database (Journals/conferences) where history look-backs shows the evolution of different input parameters range (gross rock volume, porosity, N/G ratio, permeability, saturation, fluid contacts, etc.) and hydrocarbon-in-place estimates over time and the impact of additional data on reduction of uncertainties [31]. When available, they demonstrate that the hydrocarbon-in-place uncertainty look-back approach has been highly useful in tracking the impact of new data.

There is a need for comprehensive assessment of uncertainties upfront and developing an understanding of their impact from the existing data/ information and how these uncertainties evolve with time as new data/ information is acquired. The importance of new data has been demonstrated in this section and the optimal use of existing data/information with different techniques and appropriate workflows have been elaborated in the next sections.

The example shown here is from a carbonate field in which a total of 6 wells have been drilled so far including the discovery well which demonstrates the value of new data/information. The field is a 4-way dip closure (interpreted based on 3D seismic data) bounded by the east and west side normal faults. The reservoir depth at different well locations is in the range of 4300-4500m TVDSS. Currently, this field is producing around 30,000 Bbls/day oil from 5 producers.

The predrill mean resources for this prospect were around 190 MBO. The discovery well-A encountered a gross reservoir thickness of around 128m, a net pay of 72m and a well-defined oil water contact. The well test confirmed a daily production of around 5000 Bbls/day of 30° API oil with GOR of 700scf/Bbl. Second well-B drilled, close to the eastern fault, encountered a gross reservoir thickness of around 242m, a net pay of 190m and lower OWC as compared to Well-A but indicated more reservoir heterogeneity than assumed after discovery. Well-C drilled in the centre part of the structure between two wells and it went dry. Well-D drilled towards to the west of Well-B encountered oil bearing reservoir but with a different OWC. Well-E drilled in the western part of the structure up-dip to well-A encountered oil with similar OWC as found in well-A. Well-F drilled towards the north part of confirmed the OWC of Well-B.

The primary pore system in this carbonate reservoir comprises inter-particle porosity that coexists with a highly variable secondary system of dissolution voids. As a consequence, the reservoir heterogeneity (from pore to reservoir scale) and its variability pose significant challenges to data acquisition, petrophysical evaluation, and reservoir description. The conventional petrophysical evaluations that exclusively use reservoir zonation based on the lithology/mineralogy have very limited application. For identifying the distribution of micro-porosity and its connectivity with macro-porosity, advanced down-hole technologies such as high-resolution imaging, magnetic resonance logs with advanced core analysis have proven to be very useful.

The reservoir and fluid parameters were estimated after the drilling of each well integrating previously available data (Table 1). The Original-Oil-In-Place (OOIP) for different categories (P90/P50/P10) was estimated using probabilistic approach. The OOIP uncertainty index and 2P recoverable resources were computed after each well following similar workflow of evaluation. Fig. 4 shows the summary of hydrocarbon-in-place and uncertainty changes over the appraisal and early development period. The history look-backs approach used here clearly demonstrates the effective value addition from each drilled well and the evolution of OOIP, recoverable resources including reduction in OOIP uncertainty.

Table 1. Summary of reservoir and fluid parameters estimated after each drilled well

Key parameters	Predrill	Well-A	Well-B	Well-C	Well-D	Well-E	Well-F
Reservoir Top (m)	4350	4404	4363	4456	4414	4394	4497
Gross Interval (m)	80	128	242	24	120	138	189
Net Pay (m)	56	72	190	0.0	81.5	76	87
N/G	0.70	0.56	0.78	0.00	0.68	0.55	0.46
Porosity (av.)	10%	9.5%	12.9%	6%	12%	10%	13%
Water Saturation	36%	18.3%	27%	39%	36%	22%	25%
Formation Volume Factor	1.38	1.37	1.25	1.25	1.25	1.25	1.25
Oil Water Contact (m)	-------	4532	4572	None	4505	4532	4572
Cut-offs (Vcl/Phi/Sw)		0.5/0.05/0.5	0.5/0.05/0.6	0.5/0.05/0.6	0.5/0.05/0.6	0.5/0.05/0.6	0.5/0.05/0.6
Oil API Gravity	25-30°	30°	30°		30°	30°	30°
GOR (SCF/Bbl)	500	750	670	-----	700	740	740
CO_2/H_2S Content (%)	2-5% / none	2-5% / none	2-5% / none	2-5% / none	2-5% / none	2-5% / none	2-5% / none
Gas Gravity	0.90- 1.06	0.90- 1.06	0.90- 1.06	0.90- 1.06	0.90- 1.06	0.90- 1.06	0.90- 1.06
Reservoir Pressure (psi)	6800-7648	7225	7310	-----	7268	7242	7344
OOIP (P90/P50/P10) (Millions BO)	120/635/2450	425/1874/4850	765/2450/4750	810/1890/3458	800/1503/2650	756/1070/1700	789/926/1185
RF	30%	30%	25%	18%	18%	18%	18%
P50 RR(Millions BO)	190	562	613	340	270	193	167
Uncertainty Index 1 (P10/P90)	20.42	11.41	6.21	4.27	3.31	2.25	1.50
Uncertainty Index 2 (P10-P50)/P50	2.86	1.59	0.94	0.83	0.76	0.59	0.28

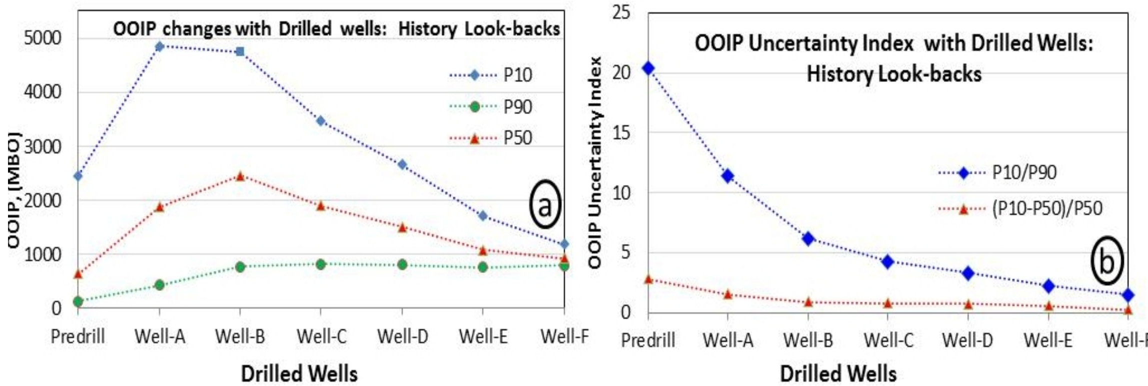

Fig. 4. (a) OOIP with analysis data and (b) Uncertainty Index (UI) with analysis data. The slope of UI curve indicates the delineation efficiency. The drilling of Wells E and F provided relatively little new information and OOIP uncertainty reduced only slightly as a result of additional data from these wells

2.3 Issues Related to Reservoir Inputs Estimation and their Distribution in 3D Static Reservoir Models

2.3.1 Petrophysical property estimation

For recognising uncertainties "what is known" as well as "what is unknown" in petrophysical parameters estimation, it is necessary to identify their basic sources of uncertainty:

2.3.1.1 Measurement accuracy

All measurements involve some degree of error or inaccuracy. The errors may be due to imprecision of the instruments or borehole effects while making the measurement, or poor calibration, or even human errors in performing the measurement. The random errors due to the basic measurement precision differences can be minimised by repeated measurements. However, identification of systematic errors or bias is critical before they can be corrected.

2.3.1.2 Incomplete or missing data

In almost every evaluation, there is missing information. Under such situations, judgment is applied and "reasonable" assumptions are made to fill the gaps. This is the area where bias effects the evaluation, which in turn reflects the personal competence and experience, preferences and motivations of the evaluator(s). Some of these biases are:

- Displacement Bias: This leads to a shift of the distribution to higher or lower values.
- Variability Bias: This is the modification of the shape of the frequency distribution curve.
- Motivational Bias: This is the conscious or subconscious adjustment of responses motivated by a perceived connection to personal rewards or punishments for certain responses.
- Cognitive Bias: This depends on an individual's mode of judgment and arises from factors such as knowledge base, mode of processing information and ability to assess the reasonableness of analogs or other inputs.

2.3.1.3 Computational approximations

Approximations inherent in the workflows and methodologies used for estimating petrophysical properties such as Vcl, effective porosity, permeability, saturation, cut-offs, and in defining the electrofacies/facies based on petrophysical properties.

To illustrate these aspects, four separate studies were performed for estimating the effective porosity in a carbonate reservoir using same log data, core data and software following similar approach shown by Meddaugh et al. [7]. These are: Study A: focused on overall match between core and log data for full field, Study B: Best overall match by well, Study C: Best match in higher porosity zones and Study D: Artificial intelligence methods using multiple logs for all the wells.

A crossplot of effective porosity values is generated between study C and other studies to show the variances (Fig. 5) for this reservoir. Porosity of around 14% will be known typically only within an error of ± 2 units. The solid line shows the 1:1 line and the dashed lines show ± 2 porosity units relative to the 1:1 line. Each approach could be technically acceptable but the variation does bring into focus the potentially large uncertainty associated with what is typically regarded as a "known" in reservoir uncertainty assessments.

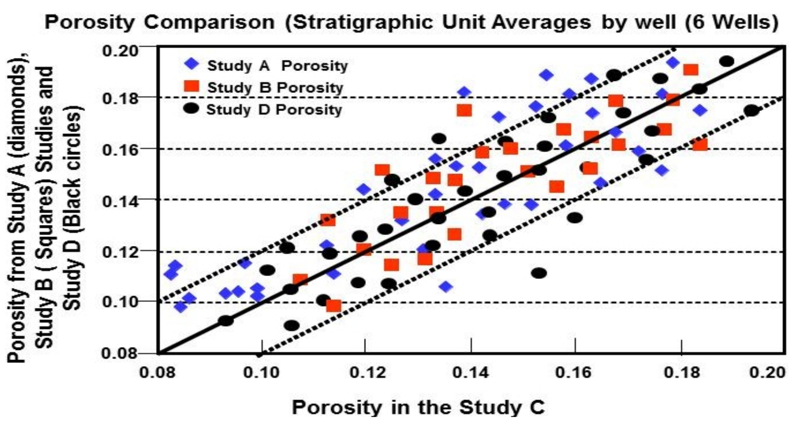

Fig. 5. Porosity comparison between three studies A, B, C and D using same data and software

The lessons drawn from this example are valid for other petrophysical properties (e.g. saturation, permeability, net reservoir and fluid contacts), although not discussed here. Therefore, it is recommended to determine uncertainties for the critical petrophysical parameters including raw data, its processing and interpretation. Most often, the largest uncertainty in petrophysical evaluation may be the interpretation model itself. The knowledge of possible ranges of petrophysical properties will improve the 3D reservoir modelling results; enabling better data gathering and study decisions.

2.3.2 Facies identification and rock typing

Most often, simple sand / carbonate shale models are generated without facies analysis. Core data is one of the critical inputs for facies classification. In absence of core, electrofacies can be used as a basis for facies identification. Well log data provide very useful information on geological concepts, stratigraphic details and petrophysical properties.

Most often, capillary pressure (Pc) curves are used in dynamic modelling as input for defining oil-in-place and vertical distribution of fluids in a reservoir. These Pc curves can have significant influence on fluids movement within a model, if not designed adequately. For a displacement process that is controlled by gravity, Pc curves control vertical saturation distribution. These Pc curves also allow definition of the top of the transition zone and its thickness which affects to control water/gas breakthroughs time and trends. Often it has been observed that these Pc curves have failed to match initial water saturation at well locations if they are not analyzed and incorporated based on proper facies / rock typing using core and log data (Figs. 6a, b and c) in the 3D reservoir models. The impact of using single rather than several rock types for water saturation can be clearly seen in Fig. 6d. In order to ensure proper fluids in place volume estimation from simulation models initializations, it is necessary to obtain an acceptable level and trend of matching between water saturation log profiles with simulation models profile for each interval within the reservoir to reduce the gap between static and dynamic models. Integration of the capillary pressure, water saturation and resistivity index results, together with the basic petrophysical data including porosity, permeability, NMR, CT scans, mercury injection and thin section images confirm the validity and consistency of the collected data and allows a more robust evaluation of the facies and rock typing.

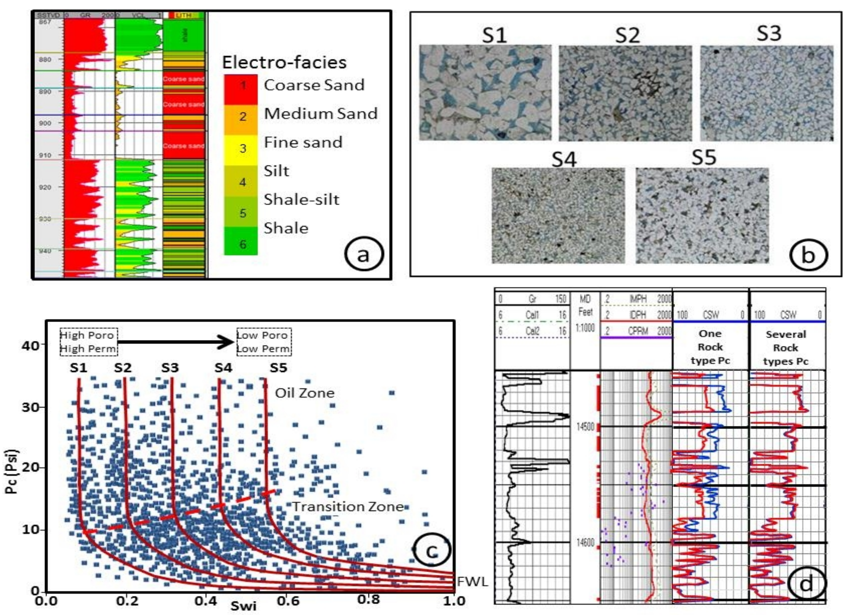

Fig. 6. (a) Electrofacies typing based on log data, (b) Rock typing based on Core data, (c) Rock typing based on Log data and (d) Comparison of capillary pressure curves derived versus log derived initial water saturation

2.3.3 Reservoir facies and property distributions

The rock and fluid properties control the volume of Original-Hydrocarbon-In-Place (OHIP) and the recoverable oil gas. Different techniques are used for populating the reservoir facies and properties in the 3D reservoir models besides geostatistics which require different types of input parameters and work under different basic assumptions. Therefore, the simulation results obtained from these techniques are highly dependent on a geomodeler's geostatistical knowledge and geological experience. For better understanding we group them in two categories:

- Variogram based techniques.
- Variogram-free techniques.

2.3.3.1 Variogram based techniques

The variogram models play an extremely important role in representing the geological knowledge in 3D static reservoir model building and in analyzing flow behaviours through dynamic simulation. Variogram, a statistical device to store patterns in a mathematical form, is a “measure of geological variability with distance” (reservoir geometry, continuity and properties) and is developed using two point statistic correlation functions [32,33]. Almost 90% of the reservoir characterization studies use variogram based geostatistical modelling methods (e.g. Sequential Gaussian Simulation (SGS), Sequential Indicator Simulation (SIS), Truncated Sequential Gaussian Simulation (TSGS), Pluri-Gaussian Simulation (PGS), etc.). These algorithms (SGS, SIS, TSGS, PGS) create a 3D model constrained to local data and the variogram model [34-36].

The SGS technique distributes reservoir properties (facies, porosity and permeability) within 3D model while honouring data at the wells and corresponding vertical and lateral correlation lengths using variograms. This technique does not constrain reservoir properties using explicit geological facies information. The variogram cannot be calculated directly from raw data of reservoir properties because SGS needs inputs to be in a normal distribution. Variograms are calculated using normal score variables. The normal score variables are later transformed back to reproduce their original distribution. Experimental variograms are calculated from the well data for normal score variables for the reservoir properties in vertical and lateral directions. This technique is most commonly used for facies distribution but does not guarantee honouring of boundary conditions and requires variograms.

The SIS technique for continuous variables divides the continuous distribution of a particular variable into a number of discrete categories. Each category represents a specific range within the continuous distribution of the attribute. The categories are distributed within the fine scale grid cell using SIS. Similar to SGS, the SIS technique does not constrain reservoir properties using explicit geological facies information. However, SIS groups similar property values together. SIS requires an indicator variogram for each category of property which are calculated for vertical and lateral directions using well data for all indicators. This technique lacks ability to honour facies boundary conditions and requires a user defined trend (variograms) to impose non-stationarity. SIS is most commonly used for petrophysical properties distribution.

The TSGS technique is used to generate the underlying geological framework of the facies. This facies framework together with SGS, is then used to distribute reservoir properties values separately within each facies. This technique honors the explicit geological facies information at the wells, vertical and lateral correlation lengths for each facies, vertical stratigraphic facies trends, reservoir properties from well data, as well as vertical and lateral correlation length of reservoir properties for each facies. This technique allows integration of both geological and petrophysical data to generate reservoir description. It works well for grain size transitions and ordered facies (e.g. carbonate environments, shoreface deposits, progradational fluvial sequences) and requires variograms as input. The TSGS technique, also known as transition modelling, allows for only strict facies boundary conditions and it becomes very unstable in the presence of high density (closely spaced) wells. Non-stationarity further compounds the problem as introduction of simple trends is often not sufficient.

The Plurigaussian simulation is an extension of the truncated (mono) Gaussian method [37,38] allowing for more complex facies relationships under a strict stratigraphic sequence. The geological information is added to the model by: number of Gaussian functions, correlation coefficient among them, facies proportion to calculate thresholds, direct and cross indicators covariances, facies data at conditioning points transformed into Gaussian rules and truncation strategy (rock type rule). There are numerous advantages of PGS over other facies simulation methods. PGS handles non-stationarity through use of multiple vertical proportion curves in the construction of a lithotype proportion matrix (LPM). The LPM consists of hundreds of high resolution trend maps accounting for vertical and lateral non-stationarity. The trends for each facies within each layer and every reservoir interval in the model are calculated. This technique is capable of capturing most inter- and intra-facies relationships including post depositional overprinting, such as diagenesis. As a pixel based method, PGS can work in the presence of closed spaced or sparse well control but is more suitable for high density well controls. However, it is important to note that PGS results are highly dependent on a geomodeler’s geostatistical knowledge and geological experience.

Depending upon the particular simulation algorithm, different types of variogram models (Nugget, Linear, Logarithmic, Gaussian, Spherical, Elliptical, Exponential, Power, etc.) are selected which require different data inputs for computing the variogram parameters (sill, nugget and range) to be used for facies and property distribution in 3D reservoir models.

However, variogram modelling and interpretation are often performed hastily or even skipped altogether. There is very little or no emphasis on understanding the variogram behaviour. Proper variogram modelling is a key factor to obtain a geologically sound reservoir characterization model. The link between geological variations and observed variogram behaviour must be understood properly for reliable variogram interpretation and modelling. After carrying out a detailed QC of input data and its distribution analysis, variogram behaviour should be related to the geological principals from direction variogram to represent the heterogeneities present in the reservoir. Some of the primary variogram behaviours are: randomness or lack of spatial correlation, decreasing spatial correlation with distance (geometric anisotropy), geological / areal trends (zonal anisotropy), stratigraphic trends and geologic Cyclicity over geologic time, etc. Real variograms almost always reflect a combination of these different variogram behaviours (Fig. 7). If the input data shows such systematic geologic trends, these trends must be modeled and removed before generating variogram models and associated input parameters to be used for geostatistical simulation. Therefore, the selection of an appropriate variogram model becomes critical for incorporating the spatial variability of geobodies, their properties and true heterogeneity present in the reservoir. For limited data cases, analog data can be used to establish variogram models [39, and references there in].

Some recommendations to develop a reasonable variogram model are:

- Perform classical statistical analysis on the data set to identify dataset issues and multiple populations. Compute mean, ranges, standard deviations, coefficient of variations etc., and create cumulative frequency distribution plots, histograms, and scattered plots of the data as necessary to gain an understanding of the nature of the element.
- Clean the data set, if required, to remove scatters and erroneous values.

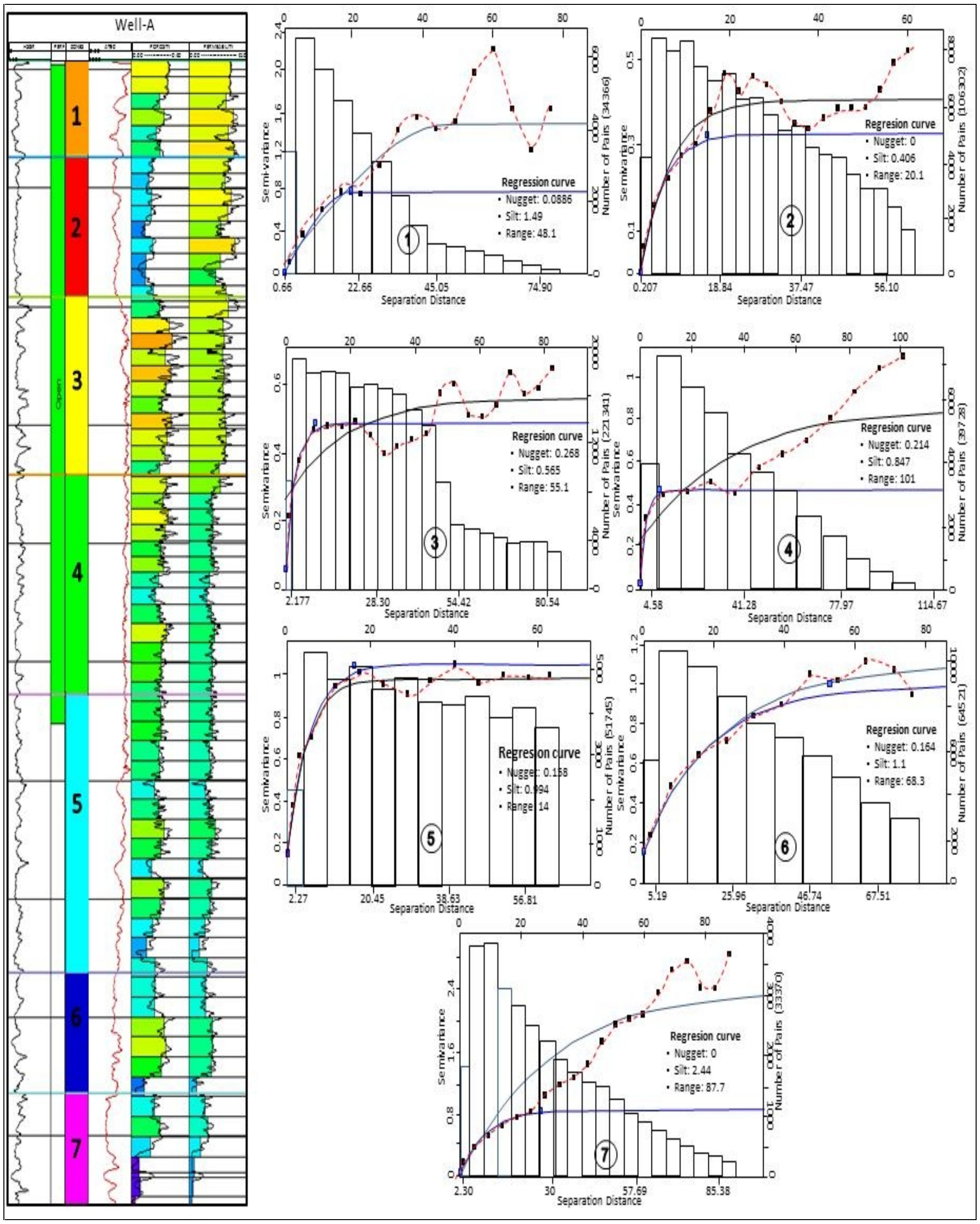

Fig. 7. Variogram behaviours of permeability data for different reservoir units showing presence of geological trends or their combinations which affect the facies and property distribution if not accounted for properly. The actual data points are connected with dotted red line to show the trend. The indices 1 to 6 indicate different stratigraphic units of a carbonate reservoir. The data points for each unit show the combination of variogram behaviours

- Analyse the spatial distribution of the data to determine the suitability for geostatistical analysis. If the data is not suitable, then perform a statistical analysis using interpolation techniques to prepare it as input for variogram modelling.
- Analyse only one variable per lithologic unit at a time and ensure that this variable is stationary over the domain of the study. If the input data has mixed population split it into subsets with unique population parameters because variogram analysis using mixed populations can produce misleading results.
- Check if the data has the same sample length i.e., sample of different size should be separated as a different groups of variogram.
- Visualise samples for irregular distributions to ensure approximately uniform sample distribution for variography.
- Transform data to standardized normal distribution (zero mean and unit variance). It simplifies the data handling and allows the comparison between different data sets.
- Follow a three step process to combine qualitative geological knowledge with quantitative variogram modelling: (1) Generate detailed interpretation of geological aspects of the reservoir, including environment, sequence stratigraphy, pore space characteristics, iso-chores, iso-porosity, and iso-permeability maps. Using these inputs, generate a summary table that includes the major continuity direction, lateral extension and anisotropy index of each attribute, (2) Calculate experimental variogram using averaging technique and (3) Model the variogram considering the information summarised in the first step.
- Generate omnidirectional / multidirectional experimental variograms and variogram maps using the procedure mentioned in the previous point to identify the nugget, sill, anisotropy and major direction of the variogram analysis. Use relevant seismic attributes to compute areal variograms, if seismic data quality is acceptable and well data to compute vertical variograms.

2.3.3.2 Variogram free techniques

Variogram based simulation techniques (e.g. SGS, SIS, TSGS, PGS) allow construction of facies and properties model conditioned to well, seismic and production data. However, simulated depositional elements do not look geologically realistic as two point statistical correlation functions are not sufficient to model curvilinear or long range continuous geological bodies. Some other techniques, which do not use variograms, are either object based or use other numerical techniques: Multiple Point Simulation [40]; Simulated Annealing [41,42,13]; Artificial Neural Networks [43,44,12]; Genetic Algorithms [45-47]; Fuzzy Logic [48-50]. Some of them are briefly described below:

<u>2.3.3.2.1 Multiple point simulation (MPS)</u>

The MPS technique, a pixel as well as an object based algorithm, aims at characterising patterns using several points (does not require variogram models), typically between 20 and 100, instead of two, thus providing more realistic representation of geological patterns. The MPS technique requires various parameters for facies dimension and geometries (thickness, length, width, orientation, etc.) and is capable of handling many wells, seismic data, facies proportion maps and curves, variable azimuth maps and interpreted geobodies. It works well for complex facies relationships but requires a large number of wells, training images (TI), outcrop mapping or any other source that produces a high resolution exhaustive model at the same scale as the simulation to capture the spatial patterns for facies and properties [51-55]. The use of TI is not compulsory for the MPS technique; the statistics can come from other sources. Nevertheless, a training image is the most convenient way of deriving the MP statistics as most desired statistics can be extracted directly with no need to fit them with positive definite models. The largest stumbling block that prevents the rapid spread of MPS in reservoir simulation tasks is the difficulty of creating TI's for each definite modelling case. A TI is a 3D conceptual model or pattern that defines the basic laws of property alternation across space and is a bridge between geological knowledge of the reservoir and the numerical model. TI's have the following requirements:

- Three dimensional spaces.
- Stationary, i.e., invariability of the statistical parameters of the TI throughout its volume. Although, now some modern MPS techniques also work with non-stationary TI's.
- Recurrence, i.e. repeated use of the same structure elements;
- Aperiodicity, i.e., no part of the TI may be an identical copy of another part of this TI; the structure elements must vary in different combinations to cover all the possible variants.
- Relative simplicity, i.e., the TI must not abound in complex structures that may not be reproduced in the realizations.
- The scale and orientation of the TI measured in grid cells are to be set according to the field being simulated.
- Statistical parameters, such as mean, variograms, unit compartmentalization (per number of cells) and dimensions of geological bodies are matched against well data and target values.

However, the implementation of the MPS technique is quite difficult. Several different approaches have been used in the industry: single and extended normal equations, neural network iterative approach, simulated annealing. As an example, the training images of porosity obtained from integration of wells and seismic data using different techniques (e.g. kriging, multi-attribute transforms using linear regression, neural networks, combination of geostatistics and neural networks), will lead to different spatial distributions, uncertainty ranges and errors [12,44], if used in MPS. Therefore, each of these methodologies has their own limitations which affect the simulation results. The MPS techniques are still an emerging area of research and require further R&D efforts to supplement the currently used traditional two-point statistics (e.g. kriging, stochastic simulations).

2.3.3.2.2 Seismic guided techniques (e.g. multi-attribute regression, principal component attributes analysis, artificial neutral networks, simulated annealing, fuzzy logic, genetic algorithms)

Currently, the industry is also using some techniques separately which allow generating lithology, porosity and permeability 3D cubes using post- and pre-stack seismic attributes derived from 3D seismic data. These 3D cubes are directly transformed into the 3D reservoir models grid and used as inputs for defining reservoir stratigraphy, populating the reservoir and nonreservoir facies along with their properties particularly away from the well locations. All these techniques use validation process through use of blind wells and newly drilled results to prove their ability to predict reservoir properties at unknown locations but comparison between them shows that level of errors and uncertainty ranges are entirely different in each technique. Therefore, proper understanding of these techniques, their assumptions and limitations are critical before using them to generate inputs for 3D reservoir modelling. Most often it has been observed that seismic data quality does not allow extracting meaningful seismic attributes which limits the use of these techniques. The details of these algorithms are beyond the scope of this paper.

It is important to note that each simulation algorithm (variogram based, non-variogram based and others) has specific input requirements, work under own basic assumptions and boundary conditions, some advantages as well as disadvantages which need to be properly understood. Under these circumstances “which one to use” or “use their combination”. In practice, a geomodeler often chooses one algorithm before another based on personal experience or competences, software capability, or some technical requirements. It is often difficult to obtain inputs for these algorithms due to limited subsurface data. Facies interpreted from well logs and core data have very high vertical resolution but very poor lateral resolution. Choosing input parameters is often subjective and the problem becomes especially severe in the lateral directions if seismic attributes are not meaningful. Several published studies have shown that use of different techniques with the same input data (well and core) provide significantly different production forecasts [7,40,53,56-58]. Therefore, a thorough understanding of the assumptions and boundary conditions for each simulation algorithm is necessary before they are used in 3D reservoir modelling.

2.3.4 Permeability measurements and upscaling

The efficient recovery of hydrocarbons relies on an accurate prediction of the fluid displacement efficiency parameters of reservoir rocks, including permeability. The description of highly homogenous reservoirs is a very simple task, as measuring reservoir properties at any location permits full description of the reservoir. However, it is not so simple for heterogeneous reservoirs, as the reservoir properties vary as a function of spatial location. For proper heterogeneous reservoir description, it is necessary to predict variation of reservoir properties of rock facies including porosity, permeability, saturation, faults and fractures as a function of spatial locations. Reservoir heterogeneity (areal and vertical) occurs at all scales from pore scale variation to major reservoir units within a field, and every scale in between. Proper identification and knowledge on various scales of reservoir heterogeneities is necessary because different scale of heterogeneities have different impact on reservoir performance, production forecasts and hydrocarbon recovery. Kelkar and Godofredo [59] have defined the scale of reservoir heterogeneities at four levels of complexities (Table 2).

Table 2. Scale of reservoir heterogeneities

Scale of Reservoir heterogeneities			
Type	**Scale**	**Measurements**	**Effect on reservoir performance**
Microscopic (Pore level)	10-100 μm	Pore and throat distribution, grain size	Displacement efficiency (trapped oil)
Macroscopic (Core Level)	1-100 cm	Permeability, porosity, saturation, wettability	Sweep efficiency (Bypassed oil)
Megascopic (Simulation grid level)	10-100m	Log properties, residual oil, seismic	Sweep efficiency (Bypassed oil)
Gigascopic (Reservoir level)	> 1000m	Well test, geological description	Extraction efficiency (Untrapped Oil)

In 3D reservoir models, the permeability variation is represented on a block-centred grid using a permeability value measured directly from core-plugs or estimated indirectly from wireline log data using predictive algorithms that relate core data intergranular permeability to porosity including some other predicting variable. The key issue is how to use micorscopic (pore throat and grain size)) and macroscopic (core) measurements without introducing artifacts due to indiscriminate transgression of scale as the volume of a typical model grid block (> 108 cm3) is several orders of magnitude greater than that sampled by a core-plug or wireline log (30-30,000 cm3). It is therefore necessary to upscale the permeability values from measurement scale to grid-block scale [60,61]. In order to fully understand the effect of sample volume on the effective single phase permeability of a heterogeneous clastic reservoir, Jackson et al. [62] have carried-out direct measurements using a large rock specimen (38x32x10 cm). They carried out measurements of permeability in different sizes of samples (starting from 1x1x1 cm to 38x32x10 cm) and observed that both individual and averaged effective permeability values vary as a function of sample volume, which indicates that permeability data obtained from core-plugs will not be representative at the scale of a reservoir model grid-block regardless of the number of measurements taken. At small sample volumes, the distributions of horizontal and vertical permeability are very broad. As the sample volume increases, both the horizontal and vertical permeability distributions narrow and converge upon the effective permeability of the entire rock specimen. They also noted that the average permeability estimated from different samples do not correspond to the effective permeability of the entire rock specimen.

To understand the permeability upscaling for highly heterogeneous carbonate reservoirs, which hosts around 50% of the world's hydrocarbons, several laboratory measurements of porosity and permeability between whole core samples and plugs drilled from the same samples have been carried out. More recently, the heterogeneity of carbonates at the pore scale using powerful image registration techniques (e.g. micro-CT, 2D SEM, 3D SEM/FIB, X-ray-CT, etc.) have been studied to characterize the fine scale structural framework of carbonates [61,63-65]. These studies indicate that permeability differences between whole core and plugs vary greatly sample to sample but whole-core permeability tends to be higher in cases where large differences (two orders of magnitude) are observed.

Different averaging upscaling algorithms (Arithmetic mean, Harmonic mean, Geometric mean) used for permeability upscaling give different results but perform reasonably well when applied to a field of permeability value covering full core-plug. The permeability upscaling becomes more critical where reservoir units have high property contrasts and is not fully represented by the available standard core-plugs. However, the error introduced by averaged data may be minimised using an appropriate averaging scheme for a given facies type and flow direction. Conventionally, the arithmetic mean is used to average the permeability measurements in the horizontal direction (parallel to the bedding), while geometric or harmonic mean is used to average permeability measurements in vertical direction (perpendicular to the bedding). This approach is based on the assumptions that each core-plug does sample only one lithology (or permeability class). In many geological systems, core-plugs generally sample a mixture of lithologies (or permeability classes) and the variations in lithology are not simply layered or uncorrelated. The most suitable averaging technique in such cases is the one which minimises the variation in mean permeability with sample volume rather than the one which yields the effective permeability of a layered or uncorrelated system. Well test data is one of the important inputs for calibrating the upscaled permeability model as well test represents the large scale permeability. However, the quality of well test data and its interpretation should always be kept in mind before using it for calibration as it is an effective permeability. The permeability upscaling from pore to reservoir and field scales in different types of reservoirs is still a challenging task and require further R&D efforts to fully understand and establish the suitable methodology.

2.4 Issues Related to 3D Dynamic Modelling

The objectives of dynamic reservoir modelling are to simulate the reservoir dynamic behaviour, forecast reservoir parameters for undrilled locations and field productivity for different development scenarios using 3D static reservoir model as an input. The simulation studies directly integrate geological parameters with engineering data (e.g. production tests, pressure data) but this integration of data requires time and an understanding of reservoir mechanisms. A basic workflow of 3D dynamic modelling consists of 5 steps: (1) data acquisition, (2) model design, (3) initialization, (4) history matching and (5) forecast. Most often, the 3D dynamic models are built separately without proper use of a 3D static model or using 3D static model that rely-on only well data and ignore the lateral and vertical heterogeneities revealed in the key seismic attributes or with a poor link between static and dynamic models. The main inputs for the dynamic models can be classified as follows:

- *Petrophysical data:-* Absolute/relative permeability, porosity, water saturation, N/G ratio, capillary pressure, rock types.
- PVT Data:- Oil properties (density, formation volume factor, gas-oil solution ratio, viscosity and saturation pressure), gas properties (gas gravity, compressibility factor, formation volume factor, viscosity) and water properties (density, formation volume factor, viscosity, compressibility).
- *Reservoir Data*:- Depth of fluid contacts, initial pressure at a given depth, temperature and aquifer parameters.
- *Production Data:-* Production / Injection fluid rates, bottom hole and tubing head flowing pressure measurements, static bottom hole pressure values.
- *Completion Data*:- Well productivity and injectivity index, wellbore diameter skin factor (i.e. permeability reduction near wellbore due to drilling and completion mud invasion).
- Well and / or field constraints:- Target (maximum) production / injection rate, maximum water rate, maximum gas-oil ratio, minimum flowing bottom hole and minimum tubing head pressure.
- *Economic Requirements:-* Minimum oil and gas production rates, maximum production rate.

Dynamic simulation workflows for Greenfield and Brownfield projects are discussed separately.

2.4.1 Greenfield 3D dynamic modelling

The uncertain production forecasts obtained from 3D dynamic simulation are particularly critical for offshore “Green Fields” where capital intensive investment decisions are taken for the field development. The risk of such decisions is that the whole development program, in many cases, is decided based on deterministic or probabilistic models built with a very limited amount of available data / information, inadequate workflows and the impact of reservoir uncertainties on predicted production forecasts is not properly captured (Figs. 8-I and 8-II). As a result, this leads to either over or under-sizing of the production facilities, impacting overall project value [66]. Depending upon the geological complexities, the appropriate methodology for dynamic simulation should use the fit-for-purpose workflow [67] shown in Figs. 8-III and 9 which allows capturing of the full spectrum of possible outcomes at an early project phase by addressing both the static and dynamic uncertainties to improve the interpretation of production forecasts.

2.4.2 Brownfields 3D dynamic modelling

History matching is a process that adjusts the model until it closely reproduces the past behaviour of a reservoir. In Brownfield projects, history matching has been identified as one of the most critical problems to affect production forecast accuracy due to uncertainty in the (1) 3D static model built using well and seismic data; (2) dynamic data (relative permeability, capillary pressure, fluid properties etc.); (3) mathematical model for flow of the fluid in the porous media particularly away from the wells and (4) production allocation (comingled production or no measurements from individual producer). It further gets complicated due to non-unique nature of the history matching solutions. Our experience in actual fields shows that in-spite of having good history matching; the production forecast hardly matches with actual production of the reservoirs. Currently, several methodologies are applied to perform a simulation model history match. Traditionally, history matching (Fig. 10-I) was performed manually through adjusting a few reservoir model parameters by a trial-and-error procedure to reproduce field performance. This process often took several months to achieve a single history matched model. For large and complex fields it was almost impossible to investigate relationships between the model responses and variations of different reservoir input parameters. Furthermore, the success of the method was largely dependent on the reservoir engineer´s experience in the specific field. The manual history match did not allow a proper assessment of the effects of uncertainties and their interaction with all the data including model assumptions used in the numerical flow model for the production forecasts.

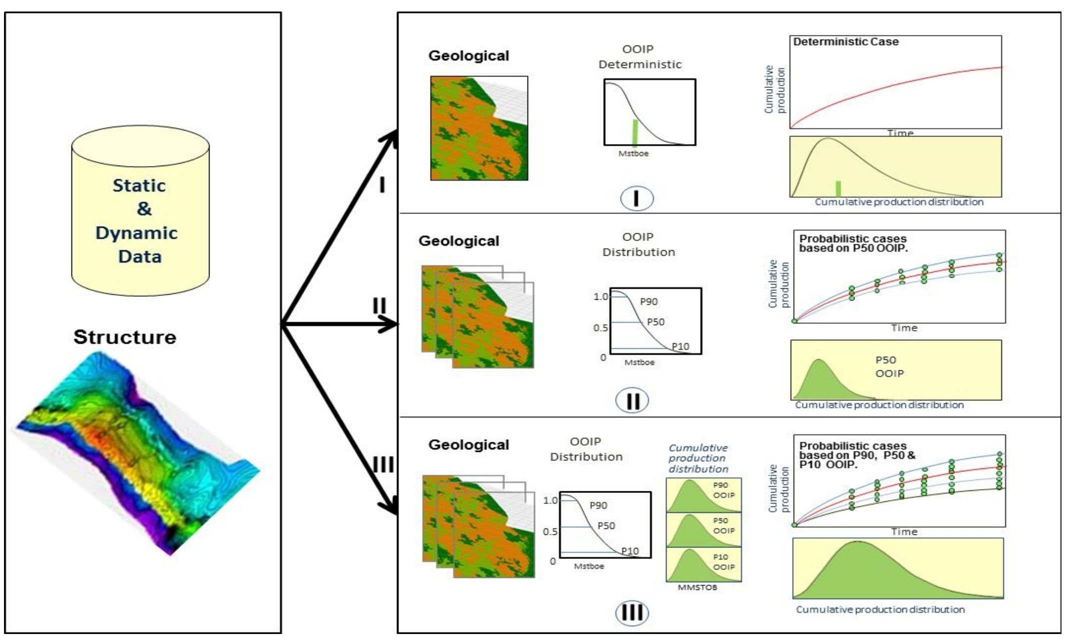

Fig. 8. Production forecast from single 3D deterministic static Model (I) using P50 OOIP without realization, (II) using P50 OOIP with realizations and (III) using P90, P50 and P10 OOIP's with realizations

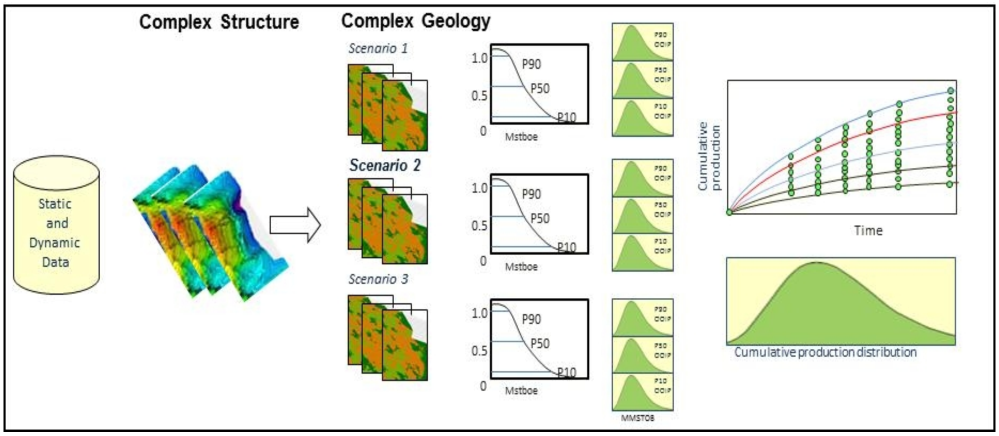

Fig. 9. Production forecasts for reservoirs having complex structure and geology. Different 3D static reservoir geological models are built and used as inputs for dynamic simulation. Final cumulative distribution was generated by combining them and capturing the full uncertainties

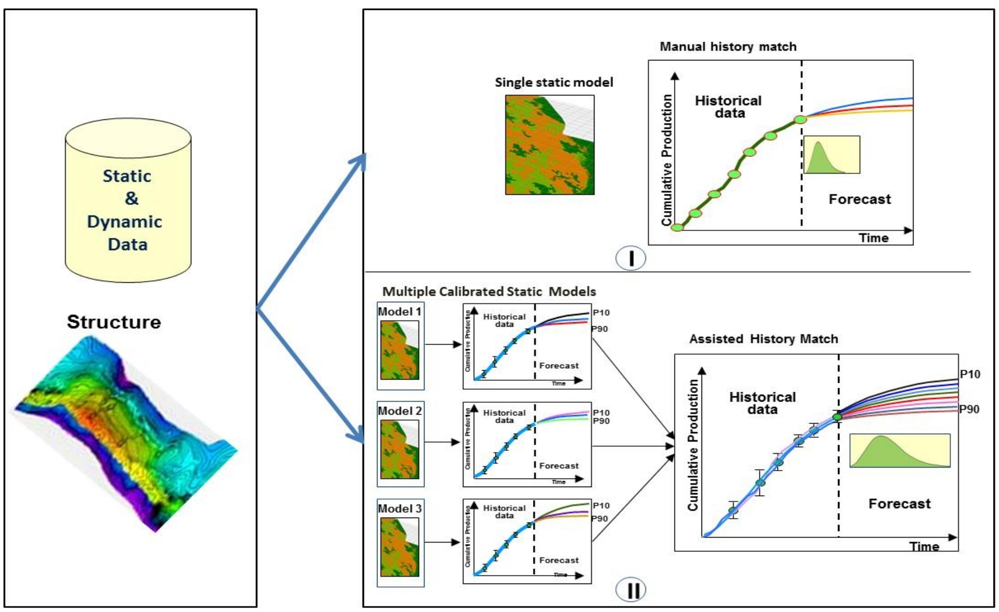

Fig. 10. Production forecasts using (I) manually calibrated 3D static and dynamic models and (II) multiple calibrated 3D static and dynamic reservoir models capturing full range of uncertainties

In order to improve the shortcoming of traditional history matching, the industry has shifted to other methods such as an Assisted or Semi-automatic History Match (ASHM) process [17] to find multiple matched models, instead of a single set of model parameters that match the data (Fig. 10-II). This helps to assess the production forecast uncertainty. ASHM is a process to compare historical and dynamic data by means of a misfit function [68]. It uses a misfit function as objective function to bind the problem with the model constraints and can generate multiple calibrated models. The major problem with ASHM is the lack of robustness and it requires different algorithms for different kinds of reservoir models. It is almost impossible to use a unique algorithm or workflow to provide an accurate match of any reservoir. ASHM technology will require some more time to become a mature technology which is more users friendly and flexible (to generate more reliable production forecasts in less time). Most of the existing algorithms have only proved to be very efficient with specific synthetic cases. But the majorities have failed or were only partially successful with real complex reservoirs.

Although, the history match process helps to understand the interactions between heterogeneity and fluid flow and gives better reliability to the static and dynamic model, a good history match does not guarantee a more accurate production forecast. Some of the recommended best practices for a good history match are:

- Know data quality, quantity and its limitations.
- Establish dynamic simulation objectives clearly and demonstrate how history match variables correspond to objectives
- Perform well and reservoir diagnostics before model construction. Diagnostics should identify reservoir vs. operational effects on production signature.
- Keep changes to a minimum, if possible. Minimum changes give higher confidence level in results.
- Larger changes can be used as an indicator for revision of the current geological model.
- Preserve geological realism using available 3D seismic and well data.
- Avoid arbitrary and ad-hoc changes. Understand the interaction between different components.
- Identify key uncertainties, rank them and analyse their impact on results. Do not smooth extremes without analyzing them in detail.
- Developing a reservoir model capable for generating a reliable production forecast of higher confidence requires a multidisciplinary team with appropriate technical skills and broad experience.

3. CONCLUSIONS

Robust integrated geological models (integrating data, process, technology and experience) following “a closed loop modelling workflow including history look-backs approach” allow close interaction between static and dynamic models to capture the full range of uncertainties in both “known” and “unknown” and their impact on production forecasts. The construction of a 3D reservoir model should be regarded as a dynamic process, subject to repeated updates as new data is made available and subject to frequent modifications when inconsistencies are found between the understandings that different specialists have about the same model. Identification, quantification and incorporation of uncertainties in 3D static and dynamic reservoir models to quantify subsurface risks are critical for improved modelling outcomes and better decision makings.

Use of an experimental design based workflow can be very helpful in identifying and ranking of the key reservoir uncertainties based on their impact at the preliminary stage of the reservoir characterization and modelling activities.

Use of more rigorous application of geostatistics (well, model), associated de-biasing techniques (analog comparison, third party reviews) and detailed QC is important to increase the confidence of the available data. Selection of appropriate variogram models incorporating zonal / geometric anisotropy, trends and cyclic geologic variations to preserve geological heterogeneities is critical for facies and property distribution in 3D static reservoir models. To assess the importance of the variogram assumptions, a sensitivity analysis of the variogram parameters should be considered as an integral part of the 3D modelling workflow.

Other simulation techniques (e.g. Multiple-Point Statistics) use trend maps/training images (instead of variogram models) to reproduce complex structures featuring curvilinearity or intricate relationship between facies, require more number of well control points to capture the spatial “patterns” of the facies and properties to be distributed within the 3D reservoir model framework. Moreover, the application of these simulation techniques is highly dependent on the geomodeler’s knowledge/ geological experience and is still an emerging area of research which requires further R&D efforts.

Use of 3D seismic attributes, if rock properties are favourable (seismic friendly), to constrain the geological models (e.g. facies and properties), particularly for fields with sparse well control points, should be considered as a part of the 3D reservoir modelling workflow. The conceptual geological model bridges the gap between reservoir geology and stochastic simulation practices. They can improve the reliability of 3D reservoir models as a prediction tool for robust production forecasts predictability and hence development concepts.

Use of upscaling QC and selection of appropriate averaging algorithms from core to reservoir scale model is important to minimize errors due to averaging. Retaining static reservoir (geological) heterogeneities in the dynamic model and considering different reservoir model scenarios for each static model (P90, P50 and P10) allows to fully capture production forecast uncertainties. Assisted history match technology is not yet fully matured despite significant progress. To obtain reasonable results, good reservoir engineering knowledge and its integration with the history match process is critical. It is important to note that simulation models are simplified representations of the highly complex geology and physics of actual hydrocarbon accumulations.

There is also a need to adopt a History Look-Backs approach for volumetric and resources/reserves evaluation to understand impact of acquired additional data/information on identified uncertainties and way forward to efficiently reduce uncertainty. These history look-backs allow calibration and continuous improvement of the quality of production forecasts over the time. The petroleum industry is, in general, moving away from an “honour the data” paradigm to “honour the data and respect uncertainty” paradigm for 3D Reservoir Modelling.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Singh V, Hegazy M, Fontanelli L. Reservoir Uncertainties assessment for Development project evaluation and Risk analysis. The Leading Edge. 2009; 28(11):272-281.
2. Wolff M. Probabilistic subsurface forecasting-what do we really know? J. Petroleum technology. 2010;62(5):86-92 (also see SPE Paper 132957).
3. Kaleta M, Essen Gijs Van, Doren Jorn Van, Bennet R, Beest Bertwim Van, Hoek Paul Van Den, Brint John, Woodhead Tim. Coupled Static/dynamic modelling for improved uncertainty handling. SPE paper 154400, presented at the EAGE annual conference and exhibition incorporating SPE Europec (4-7 June 2012), Copenhagen, Denmark.
4. Obeta CC, Ugonoh MS, Ajayi OC, Sijpesteijn CK. Reducing field development risk in marginal assets through Probabilistic Quantification of Uncertainties in Estimated Production Forecast-TsekelewuStudy. SPE paper 163005, presented at the Nigeria Annual International Conference and Exhibition (6-8 August 2012), Abuja, Nigeria.
5. Rose PR. Delivering on our E&P promises, The Leading Edge. 2004;23(2):165.
6. Merrow EW. Oil industry megaprojects: our recent track record. OTC paper 21858 presented at the OTC (2-5 May, 2011), Houston, Texas, USA.
7. Meddaugh WS, Campenoy N, Terry Osterloh W, Tang Hong. Reservoir forecast optimism-Impact of geostatistics, reservoir modelling heterogeneity, and uncertainty. SPE paper 145721 presented at the SPE Annual Technical Conference and Exhibition (30 October-2 November 2011), Denver, Colorado, USA.
8. Al-Jenaibi Faisal, Salameh Lutfi A, Recham R, Meziani S, Bader Saif Al-badi, Adli M. Best practice for static and dynamic modelling and Simulation “History match case-Model QA/QC criteria for reliable predictive mode”. SPE paper 148279, presented in reservoir characterization and simulation conference and exhibition (9-11 December 2011), Abu-Dhabi UAE.
9. Dogru AH, Fung LSK, Middya U, Al-shaalan TM, Pita JA, Hemant Kumar K, Su HJ, Tan JCT, Hoy H, Dreiman WT, Han WA, Al-Harbi R, Al-Youbi A, Al-Zarnel NM, Mezghani M, Al-Mani T. A next generation parallel reservoir simulator for giant reservoirs. SPE Paper 119272, presented in SPE reservoir simulation symposium (February 2-4, 2009), The Woodlands, Texas, USA.
10. Singh V, Srivastava AK. Understanding the seismic resolution and its limit for better reservoir characterization. Geohorizons. 2004;9(2):5-36.
11. Kim Y, Ji J, Yoon KJ, Wang B, Li Z, Xu W. The future of seismic imaging, reverse time migration and full wavefield inversion-Multistep Reverse Time Migration. OTC Paper 19875 presetned at the Offshore Technology Conference (2-5 May 2011), Houston, Texas, USA.
12. Singh V, Srivastava AK, Tiwari DN, Painuly PK, Chandra Mahesh. Neural Networks and their Applications in Lithostratigraphic interpretation of seismic data for reservoir characterization. The Leading Edge. 2007;26(10):1244-1260.

13. Grana D, Paparozzi E, Mancini S, Tarchiani C. Seismic driven probabilistic classification of reservoir facies for static reservoir modelling: a case history in the Barents Sea. Geophysical Prospecting, 2012; (online published on October 18).
14. Dogru AH. Giga-cell Simulation, Saudi Aramco J. of Technology 2011 (Spring): 2-8.
15. Baker RO, Chugh S, Mcburney C, Mckishnie R. History matching standards; quality control and risk analysis for simulation. Paper number 2006-129, Canadian International Petroleum Conference. 2006:1-16.
16. Benetatos C, Viberti D. Fully integrated hydrocarbon reservoir studies: Myths or Reality? American J. of Applied Sciences. 2010;7(11):1477-1486.
17. Cancelliere M, Verga F, Viberti D. Benefits and limitations of assisted history matching. SPE paper 146278, presented at SPE offshore Europe Oil and Gas Conference & Exhibitions (6-8 September 2011), Aberdeen, UK.
18. Friedmann F, Chawathe A, Larue DK. Assessing Uncertainty in Channelized Reservoirs Using Experimental Designs. SPEREE. 2003;264.
19. White CD, Royer SA. Experimental Design as a Framework for Reservoir Studies," SPE 79676, presented at SPE Reservoir Simulation Symposium during 3-5 February 2003, Houston, Texas, USA.
20. Mason RL, Gunst RF, Hess JL. Experimental design and analysis of experiments with application to engineering and science. Second Edition, Wiley-Interscience; 2003.
21. Narahara GM, Spokes JJ, Brennan DD, Maxwell G, Bast M. Incorporating Uncertainties in Well-Count Optimization with Experimental Design for the Deep-water Agbami Field. SPE paper 91012, presented at SPE Annual Technical Conference and Exhibition (26-29 September 2004), Houston, USA.
22. Cheong YP, Gupta R. Experimental design and analysis methods for assessing volumetric uncertainties. SPE Journal. 2005;(September issue):324-335.
23. Cebastiant A, Osbon RA. Experimental design for resource estimation: A comparison with the probabilistic method. SPE Paper 147542, presented at SPE reservoir characterization & simulation conference and exhibition (9-11October 2011), Abu Dhabi, UAE.
24. Cyril O. Avoiding misleading performance predictions for a reservoir system with limited production data by the application of experimental design technology. SPE paper 150747, Nigeria International Conference and Exhibition (July 30 - Aug 3, 2011), Abuja, Nigeria.
25. Joosten G, Altintas A, De Sousa P. Practical, operational use of Assisted History Matching and Model Based Optimization in the Salym Field. SPE Paper 146696, presented at the SPE Annual Conference and Exhibition (30 October – 2 November, 2011), Denver, Colorado, USA.
26. Haldorsen HH, Demsleth E. Stochastic modelling. J. Petroleum Technology, 1990;40(4):404-412.
27. Campozana FP, Backheuser Y, Antunes RF, Camoleze Z. Stochastic modelling and uncertainty analysis of mature fields. SPE Paper 108274 presented at Latin American and Caribbean Petroleum Engineering Conference and Exhibition (15-18 April 2007), Buenos Aires, Argentina.
28. Allan PD. Stochastic analysis of resource plays: maximizing portfolio value and mitigating risks. SPE Journal of Economics and Management. 2011;(July):141-148.
29. Rose PR. Measuring what we think we have found: Advantages of probabilistic over deterministic methods for estimating oil and gas reserves and resources in exploration and production, AAPG Bull. 2010;V-91(1):21-29.
30. Malhotra V, Lee MD, Khurana A. Decisions and uncertainty management: Expertise matters. SPE Paper 88511, SPE Asia Pacific Oil and Gas \conference and Exhibition (18-20 October, 2004), Perth, Australia.

31. Meddaugh WS, Griest S, Barge D. Quantifying uncertainty in carbonate reservoirs - Humma Marrat Reservoir, Partitioned Neutral Zone (PNZ), Saudi Arabia and Kuwait. SPE paper 120102, presented at SPE Middle East Oil & Gas Show and Conference (15–18 March 2009), Kingdom of Bahrain.
32. Gringarten E, Deutsch CV. Methodology for variogram interpretation and modelling for improved reservoir characterization. SPE paper 56654 presented at SPE annual technical conference and exhibition (October 3-6, 1999), Houston, Texas, USA.
33. Bahar A, Ates H, Kelkar M, Al-Deeb M. Methodology to incorporate geological knowledge in variogram modelling. SPE Paper 68704, presented at SPE Asia Pacific Oil and Gas Conference and Exhibition (17-19 April 2001), Jakarta, Indonesia.
34. Deutsch CV, Journel AG. GSLIB: Geostatistical software library and user's guide. 2nd edition, Oxford, Oxford University Press, New York, USA, 350 pages; 1998.
35. Doligez B, Chen L. Quantification of uncertainties in Volume In Place using geostatistical approaches, SPE paper 64767, presented at SPE International Oil and Gas conference & Exhibition (7-10 November, 2000),Beijing, China.
36. Deutsch CV. Geostatistical reservoir modelling. Oxford University Press, New York, USA. 2002;376.
37. Armstrong A, Galli A, Le Loe'h G, Geffrey G, Eschard R. Plurigaussian Simulations in Geosciences, Springer publications; 2003.
38. Remacre AZ, Zapparolli Luis H. Application of the Plurigaussian simulation technique in reproducing lithfacies with doublé anisotropy, Revista Brasileira de Geociencias, 2009;33(2- supplement):374-42.
39. Kupfersberger H, Deutsch CV. Methodology for integrating analog geologic data in 3D variogram modelling, AAPG Bull. 1999;83(8):1262-1278.
40. Larriestra CN, Gomez H. Multiple-point simulation applied to uncertainty analysis of reservoirs related to high sinuosity fluvial systems: Mina El Carmen Formation, San Jorge Gulf Basin, Argentina. Expanded abstract, presented at AAPG international conference & exhibition (15-18 November, 2009), Rio de Janeiro, Brasil.
41. AlQahtani G, Vadapalli R, Siddiqui S, Bhattacharya S. Well optimization strategies in conventional reservoirs. SPE Paper 160861, presented in SPE Saudi Arabia section Technical Symposium and Exhibition (8-11 April 2012), Al-Khobar, Saudi Arabia.
42. Li S. An improved simulated annealing algorithm based on genetic algorithm, Advanced Materials Research. 2012;(490-495):267-271.
43. Hampson D, Schuelke J, Quirein J. Use of multi-attribute transforms to predict log properties from seismic data. Geophysics. 2001;(66):220–236.
44. Pramanik AG, Singh V, Vig Rajiv, Srivastava AK, Tiwari DN. Estimation of effective porosity using geostatistics and multi-attribute transforms: A case study. GEOPHYSICS. 2004;69(3):352-372.
45. McCormack MD, Stoisits RF, MacAllister DJ, Crawford KD. Applications of genetic algorithms in exploration and production, The Leading Edge. 1999;18(6):716-718.
46. Mallick S. Some practical aspects of pre-stack waveform inversion using a genetic algorithm: An example from east Texas Woodbine gas sand: Geophysics, 1999;64:326–336.
47. Emerick A, Eugênio Silva, Bruno Messer, Almeida Luciana F, Szwarcman Dilza, Pacheco Marco Aurélio C, Marley MBR. Well Placement Optimization Using a Genetic Algorithm with Nonlinear Constraints. SPE paper 118808, SPE Reservoir Simulation Symposium (2-4 February 2009), The Woodlands, Texas, USA.
48. Lim J, Kim J. Reservoir porosity and permeability estimation from well logs using Fuzzy Logic and Neural Networks, SPE paper 88476, presented at SPE Asia pacific oil and gas conference and exhibition (18-20 October 2004), Perth, Australia.

49. Bagheri AM, Biranvand B. Characterization of Reservoir Rock Types in a Heterogeneous Clastic and Carbonate Reservoir. JUST. 32(2):29-38.
50. Zellou AM, Ouenes A. Integrated fractured reservoir characterization using neural networks and Fuzzy logic: three case studies. J. Petroleum Geology, 2007;24(4):459-473.
51. Krishnan S, Journel AG. From Variogram to multiple point measures: Mathematical Geology. 2003;36(8):945-964.
52. Arslan I, Rebeiro MT, Al Neaimi M, Hendrawan I. Facies modelling using multiple-point statistics: An example from a carbonate reservoir section located in a small part of a large shelf margin of Arabian Gulf, UAE. SPE paper 118089 presented at Abu Dhabi International Petroleum Exhibition and Conference (3-6 November 2008), Abu Dhabi UAE.
53. Liu Yuhong, Atan S. A study of static modelling factors that are critical to flow simulation, IPTC paper number 12894, International Petroleum Technology Conference (3-5 December 2008), Kuala Lumpur, Malaysia.
54. Bezrukov AV, Davletova AR. Methods of multiple-point statistics in geological simulation practice. SPE paper 135911, presented in Russian Oil and Gas conference and Exhibition (26-28 October 2010), Moscow, Russia.
55. Boucher A. Strategies for modelling with Multiple-point simulation algorithms. Closing the gap-2011, Gussow Geoscience conference (October 3-5, 2011), Benff, Alberta.
56. Hand JL, Yang C, Chopra AK, Moritz Jr. AL. Ability of geostatistical simulations to reproduce geology: A critical evaluation. SPE paper 28414, presented at SPE Annual Technical Conference and Exhibition (25-28 September 1994), New Orleans, USA.
57. Journel AG, Gundeso R, Gringarten E, Yao T. Stochastic modelling of a fluvial reservoir: a comparative review of algorithms, J. Petroleum Science & Engineering, 1998;21:95-121.
58. Alquassab H, Vaughan L. Impact of facies modeling on reservoir performance forecasting: a comparison between discrete modelling and mixed lithology approaches, SPE paper 163293 presented at SPE Kuwait international petroleum conference and exhibition (December 10-12, 2012), Kuwait city, Kuwait.
59. Kelkar M, Godofredo P. Applied Geostatistics for reservoir characterization, Published by Society of Petroleum Engineers (SPE); 2002.
60. Haldorsen HH. Simulator parameters assignment and the problem of scale in reservoir engineering, in L.W. Lake and H.B.Catroll edited Reservoir characterization: Academic Press, London. 1986:393-340.
61. Khalili AD, Arns CH, Arns JY, Hussain F, Cinar Y, Pinczewski WV, Latham WS, Funk J. Permeability upscaling for carbonates from the pore scale using multiscale xray-CT Images, SPE Paper 152640, SPE/EAGE unconventional resources conference and exhibition (20-22 March 2012), Vienna, Austria.
62. Jackson MD, Muggeridge Ann H, Yosida Shuji, Johnson Howard D. Upscaling permeability Measurements within complex heterolithic tidal sandstones. Mathematical Geology. 2003;35(5):499-520.
63. Honarpour MM, Djabbarah NF, Sampth K. Whole core analysis-Experience and challenges, SPE reservoir evaluation & engineering. 2005;8(6):460-469.
64. Ehrenberg SN. Whole core versus plugs: Scale dependence of porosity and permeability measurements in platform carbonates, AAPG Bull. 2007;91(6):835-846.
65. Serag El Din S, Dernaika MR, Al Hosani I, Hannan L, Skjaeveland SM, Kalam MZ. Whole core versus plugs: Integrating log and core data to decrease uncertainty in petrophysical interpretation and STOIP calculations, SPE 137679, presented at Abu Dhabi International Petroleum Exhibition & Conference (1-4 November 2010), Abu Dhabi, UAE.

66. Pippe O, Mayall M, Chandler M, Dodd T, Reid P, Taylor P. Ultra deep water subsalt reservoir characterization: An integrated multi-scenario approach for development planning, SPE paper 142280, SPE Annual Conference and Exhibition (23-26 May 2011), Vienna, Austria.
67. Schulze-Riegert R, Ghedan S. Modern Techniques for History Matching. Presented at 9th International Forum on Reservoir Simulation (December 9 – 13, 2007), Abu Dhabi, UAE.
68. Al-akhdar S, Ding DY, Dambrine M, Jourdan A. An Integrated Parameterization and Optimization Methodology for Assisted History Matching: Application to a Libyan Field Case, SPE paper 150716. Presented at the SPE North Africa Technical Conference and Exhibition (20-22 February 2012), Cairo, Egypt.

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