Reservoir Technologies of the 21st Century

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Foreword

Although it has been more than 150 years since Colonel Drake successfully drilled and completed the first productive and self-sustaining oil well in Pennsylvania in 1859, the reservoir technical discipline has remained very conservative and been resistant to change. It generally only does so when forced to by external events—such as when taxation practices led to the development of decline curve analyses in the 1910s and 1920s, regulatory proration practices led to the development of deliverability testing (and inflow performance relationships) in the 1930s, and the unitization practices of the 1950s led to the development of reservoir modeling and simulation. Despite the more-recent claims of integrated reservoir studies and although the circular references in most workflows imply an iterative model-building approach, these processes are typically a mere fine-tuning of the quality and quantity of a select set of model parameters. Seldom does a workflow lead to a new perception of a reservoir.

Technical and operational improvements in the past several decades have significantly increased the efficiency of reservoir management. However, there have been no major breakthroughs leading to substantial improvements in recovery factors, which remain below 30% (except in very-high-quality reservoirs) and drop to a mere 5 to 8% in unconventional (or low-quality) reservoirs. The contribution of 375 enhanced oil recovery (EOR) projects worldwide to global oil production was only approximately 2% in 2017 and is expected to rise to 4% by 2040 (McGlade et al. 2018). One of the underlying reasons for this asymmetry between the interest in EOR and its actual impact is that EOR ideas have not changed much, categorically, since the 1970s, despite the increased complexity of target formations, the availability of more-effective EOR agents, and significant technological improvements for implementation.

This lack of progress has resulted from many factors, including the interest in shorter-term project economics, the scarcity of technical and human resources, a lack of motivation, and an insufficient knowledge base from which to direct improvements in reservoir technology. New developments such as data analytics, artificial intelligence, and machine learning and the availability of advanced computing and software capabilities have provided and will continue to provide better tools to develop new ideas and technologies. However, there are also concerns that the "big crew change" will erode the foundational knowledge and rich human experience that have been built over the past 150 years. A related problem stems from the mesmerizing capabilities of computerized tools (software, simulators, artificial intelligence) and the irresistible convenience of automated analysis packages, which require minimal human intervention. In a discipline where the nonuniqueness of solutions is inherent, ensuring the physical consistency of the interpretation is the only defense against committing gross errors. This requires that the user or interpreter be proficient in the physics of reservoir phenomena and have an ability to incorporate multidisciplinary data into the interpretation process. Unfortunately, the computerized analysis tools available today are sometimes used with absolute trust and without sufficient experience and understanding of the background. In most of these cases, the tools and the theory are blamed for any failures.

Finally, many theoretical and technological innovations that were developed outside of petroleum science and engineering in the past several decades have not been adequately explored or adopted. Despite easier access to broader knowledge, our interest and focus appear to have narrowed to the discipline-specific knowledge, practice, and experience documented in petroleum science and engineering publications. Moreover, a review of the technical papers available in the OnePetro library and the SPE Forum Series topics, much less those of the technical conferences and workshops, reveals the dreaded reality: We have been entertaining the same concepts over and over instead of introducing new ideas, or discussing how existing tools can be tweaked to perform new tasks instead of developing new technologies for our changing needs.

To tackle these current and future challenges, the SPE Reservoir Advisory Committee (RAC) began an initiative in May 2019 to develop a comprehensive strategic plan to review, revise, and update the reservoir technical discipline, with the following specific objectives:

- Initiate a critical review and discussion to identify old, obsolete, inadequate, and/or irrelevant technologies
- Encourage the development of candidate concepts to replace old perceptions and technologies
- Propose, discuss, establish, and disseminate new concepts and technologies
- Educate and train the workforce to manage the transformation of industry practices

For this initiative, the RAC—which comprises 56 subject-matter experts—was organized into study groups to focus on the following three categories and their associated subcategories:

- Reservoir characterization
  - Geology, geophysics, petrophysics, rock physics, and geomechanics
  - Core analysis
  - Pressure transient analysis
  - Rate transient analysis
- Reservoir engineering
  - Fluid flow in porous media
  - Phase behavior and PVT analysis
  - Molecular- and pore-scale modeling
  - Field-scale numerical reservoir simulation
  - Enhanced oil recovery
  - Well performance
- Reservoir management
  - Data analytics, artificial intelligence, and machine learning
  - Field-scale projects
  - Reserves
  - Project economics

The resulting green paper, which is presented here, is not envisioned as an authoritative document but rather a candid, as well as provocative, account of the state of the reservoir discipline. (For the purpose of this work, the term "green paper" describes a tentative report/consultation document with technical proposals prepared for discussion.) As a general disclaimer, this work is not intended to be an SPE position statement, nor is it an SPE board report. The opinions presented in this document belong solely to the contributing authors, not to their affiliated organizations. Moreover, consensus on opinions was not sought among the contributors beyond the requirement of reasonable factual support. Rather, it is an attempt by a group of subject matter experts to inspire discussion regarding the reservoir technologies that will be required to meet the challenges of the

21st century. Any appearance of promoting a particular technology, concept, model, or approach is completely unintentional. Contributors selected topics based on their expertise on and/or familiarity with those topics; the exclusion of any topic might be merely an omission. To adhere to our objective to generate discussion, rather than to solve problems, no effort was made to be detailed or comprehensive. References have been included when the authors believed it was relevant to give credit to the original source of a specific concept or technology, but we tried to limit references because we do not wish to guide the reader in a specific direction.

Finally, my acknowledgments are due to the key participants of this project. The support and contributions of my Reservoir Technical Director predecessors, Olivier Houze (2012–2015) and Tom Blasingame (2015–2018), have been greatly appreciated. They provided much-needed encouragement and excellent editorial contributions throughout the process of bringing this document together. I was fortunate to work with a distinguished group of subject-matter experts, the members of the 2018–2021 SPE RAC, on the technical content of the green paper. I am indebted to their dedication to support SPE's mission "to collect, disseminate, and exchange technical knowledge concerning the exploration, development, and production of oil and gas resources" and vision to "advance the oil and gas community's ability to meet the world's energy demands in a safe, environmentally responsible, and sustainable manner" in the 21st century. Melinda Mahaffey Icden has been an invaluable asset during the final editing of this document, which was written by a large and eclectic group of authors with diverse backgrounds, to ensure format consistency and enhance content clarity and readability. And, of course, I am thankful for the resources provided by SPE to bring this project to fruition.

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Reservoir Characterization

Introduction

From an empiricist perspective, reservoir characterization is the practice of defining reservoir qualities by means of the measurement or appraisal of a selected set of tangible quality identifiers. From a utilitarian perspective, however, reservoir characterization serves to describe the flow domain and quantify the constitutive relations of flow; that is, appropriate values are assigned to the characteristic parameters, with the objectives of modeling flow and predicting recovery. In this utilitarian view, the characteristics of the reservoir to be defined, qualified, and quantified are dictated by the perceived reservoir flow process and the selected phenomenological descriptions of transport. In turn, characterization, combined with knowledge of the fundamental laws of physics, shapes our assumptions of the reservoir flow process. Thus, the evolution and the current status of reservoir characterization are not independent of the evolution of our perceptions of the reservoir flow processes and the current needs of our reservoir engineering and management practices. Moreover, the information used for reservoir characterization comes from diverse sources—such as seismic, well logs, cuttings, cores, pressure and rate transient tests, and production performance—and integrates specialties embedded in geology, geophysics, and engineering. Therefore, the decision to devote a separate section to reservoir characterization that covers geosciences (geology, geophysics, petrophysics, and geomechanics), core analysis, pressure transient analysis, and rate transient analysis was made solely for convenience in terms of organizing, documenting, and referencing the discussions in this green paper.

Geology, Geophysics, Petrophysics, Rock Physics, and Geomechanics

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Introduction

Most subsurface disciplines are based on methods that were initially derived from investigated conventional rocks (greater than 15% total porosity and 1-md permeability). The industry then refocused its activities on coalbed methane, then on shale gas, and then recently on tight liquids in siltstones, shales, and carbonates (Passey et al. 2010). Currently, the industry is tackling tight oil in all rock types with equations, concepts, and principles that are known to be unreliable for measuring and quantifying the storage and production behavior of these defined unconventional reservoirs (Dean and Stark 1920; *API RP40* 1998).

Geological, petrophysical (including geomechanics), geophysical, and geochemical disciplines all help to focus and support in-place to producible hydrocarbon assessments and quantification, reservoir- to production-scale engineering, and in general upstream, midstream, and downstream efforts in the oil and gas industry. Empirical solutions have been proven to work over a wide range of reservoir rock types and stratigraphic conditions (Clavier et al. 1984; Comisky et al. 2007). However, they require modifications beyond what they were intended for, which gives rise to myriad solutions that can turn petrophysics and geophysics into an art more than a science. A reliance on empirical solutions that work in one reservoir but are difficult to extrapolate could be minimized by focusing future work on fundamental research. It would be beneficial to go back to the drawing board, bringing earth scientists, physicists, chemists, and mathematicians together to look at rocks and fluids using modern laboratory and computational methods. In the age of parallel computing, cloud solutions, and sophisticated laboratory measurements, this should be much easier to do today than 10 years ago.

One issue is financial support, combined with a focus on a short-term, rather than a long-term, vision. A significant number of oil companies have eliminated fundamental research. They now depend on the service companies to improve the means of production through applied research techniques and methods. Among such improvements are optimized drilling methodologies and advanced measurement while drilling and logging while drilling, as well as openhole, casedhole, and production logging wireline/cable measurements. Service companies often partner with universities in this process, and while a significant amount of fundamental work is being performed at universities, academically driven foundational research work tends to receive less industry support. The affiliated professional societies [such as SPE, the Society of Petrophysicists and Well Log Analysts, the American Association of Petroleum Geologists, and the Society of Exploration Geophysicists] could lead by coordinating support for programs and workshops considered to be industry-advancing studies.

History, Background, and Original Concepts

Reservoir models are built on the basis of reservoir characterization, which includes the geological definition and boundaries, gross/net isopach maps, and the distribution of petrophysical properties such as porosity, permeability, relative permeability, and fluid saturations. Lately, unconventional reservoir development has also emphasized sweet-spot delineation—which involves mapping temperature, pressure, and fluid distributions—and the definition of aspects such as structure, fractures, stratigraphy, and facies.

The characterization of conventional reservoirs has been ongoing for more than 50 years, but the characterization of unconventional reservoirs can still be considered to be in its infancy. Knowledge of reservoirs (carbonate, clastic, and shale) continues to improve with time and the evaluation of techniques. Current technology and practice enable the qualitative and quantitative characterization of depositional environments, facies, flow units, geomechanics, total organic carbon (TOC) distribution and type, and porosity/permeability types to aid reservoir/resource exploration and development. Fracture network modeling has emerged as an area of interest with the recognition of fractures as key petrophysical features defining flow and the recovery characteristics of reservoirs. The description and characterization of major fracture sets are frequently based on fractal models and/or on geostatistical criteria.

Historically, the primary role of petrophysics was to recommend data-collection programs and quantify hydrocarbons-in-place as indicated by openhole wireline tools. Over the years, its role has expanded, as has that of other disciplines (geophysics, geology/stratigraphy, geochemistry, basin modeling), to encompass many subjects, with countless tools used to address these subjects and move from qualitative to quantitative solutions or evaluations (Capsan and Sanchez-Ramirez 2016). The role had been seemingly siloed from integration with other disciplines as most petrophysicists were focused on the active operational components of logging a given vertically oriented wellbore and the

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Conventional reservoirs have been characterized for more than 50 years, but the characterization of unconventional reservoirs is still in its infancy. Knowledge of reservoirs continues to improve with time and the evaluation of techniques.

The role of petrophysics has expanded, with countless tools available to move from qualitative to quantitative solutions or evaluations. The industry has started to move beyond initial prototypes and laboratory instrumentation designs by advancing newer techniques.

The perception of shale has changed, and its dynamic complexity is now recognized.

It became evident that new tools and innovative development were needed to better support the geological, geophysical, and petrophysical understandings and assessments of unconventional formations.

quality control and interpretation of the acquired data (Archie 1942; Waxman and Smits 1968; Juhasz 1981). Now, data are routinely acquired in vertical, deviated, and horizontal wellbores (Elkington et al. 2002; Market et al. 2016). Basic static laboratory measurements were used to define storage and flow as well as to confirm hydrocarbons-in-place using the Dean-Stark method. Integration with geochemical measurements such as TOC and programmed pyrolysis was still being developed and standardized into the late 1990s and early 2000s (Jarvie 1991; Behar et al. 2001; Carvajal-Ortiz and Gentzis 2015). The industry has now started to move beyond those initial prototypes and laboratory instrumentation designs by advancing techniques such as standard crushed-rock analysis and retort methodology, permeability techniques, and geochemical modifications and focusing on rock and fluid quantification (Maende et al. 2017; Durand et al. 2019).

Geologists dominantly relied on basic openhole wireline suites and seismic volumes for sequence stratigraphic interpretation and the development of depositional frameworks (Bohacs and Lazar 2010; Bohacs et al. 2011, 2014). Basic properties were mapped in 1D and 2D for sweet-spot identification by overlaying key geological properties for potential hydrocarbon accumulations. Also critical were a structural understanding of trap and seal analysis focused on conventional reservoir connectivity and volumetric assessment of the “size of the prize.” The general understanding of the dynamic complexity in shale—or, more specifically, mudstone deposition—left a lot to be desired. The assumed model was one of consistently homogeneous drapes with no geological architecture or significant variation in organic matter type or presence. The primary concern was that there was shale somewhere and it was generating hydrocarbons, and within the basin it generated the top seal to conventional systems. Now, the conventional reservoir seal is the new reservoir and has important variations and changes that lead to varying horizontal drilling performance and production.

The understanding of carbonates and tight sands was also overly simplistic, where widely applied global models that assumed one tight carbonate was the same as any other were used for the sake of consistency despite subsurface variability. However, through whole-core acquisition and outcrop studies over the years, it has become evident that this might not be the case. Using the basic available tool suite(s) for all disciplines resulted in scientific and discipline-specific limitations. Techniques and methods needed to be updated to be applicable to unconventional formations and principles for rock and fluid interactions (Comisky et al. 2011; Handwerger et al. 2011). New tools and innovative development were needed to better support the geological, geophysical, and petrophysical understandings and assessments of unconventional formations.

Current Status

The current technologies for the measurement and characterization of petroleum fluids, the procedures to delineate depositional systems, and the methods to measure porosity and permeability are still acceptable. In fracture analysis and structural characterization, however, many misperceptions and obsolete approaches can be found. In geophysics, the main challenge has been seismic amplitude preservation. As we deal with more-complex structures, building velocity models and imaging become more pressing. Many challenges also exist for complex near-surface conditions. For unconventional reservoirs, for example, subtle reservoir impedance changes can still present difficulties for quantitative inversion.

Hydrocarbon-system applied understandings no longer consider the single-layer, constant subsurface property application of unconventional rock types but rather the complex, interbedded nature of these unconventional formations and variability in the rock and fluid interactions over time. Rather than rely on assumptions, time/temperature constraints are now focused on data collection using developed techniques specifically applicable to unconventional rocks spanning various play types. The focus of the geology, geochemistry, and petrophysics disciplines has shifted toward defining kerogen type, TOC enrichment or leanness, thermal maturity vs. time, and the distribution of organic matter, which influence qualitative and quantitative efforts. The geological characterization of sequence stratigraphic frameworks has been rejuvenated because of the complexity observed in shales (Passey et al. 2010). No longer are mudstones considered to be a homogeneous shale drape at the toe of a turbiditic sequence. Rather, the best practice is to pay close attention to the depositional environment of the lean or enriched organic matter within the fine-grained rock column (Bohacs et al. 2011).

In addition, comparing and contrasting elemental compositional information to and with 2D/3D maps and predicting where upwelling environments might exist or if a basin ever went anoxic or dysoxic are critical details now able to be interpreted from data generated using laboratory instruments and applied discipline methodology, unraveling the unconventional play types. Seismic volumes are being used to understand and constrain the rate of the depositional slope and how regionally extensive the maximum floods vs. boundary sequences are and how they influence the source-rock distribution, enrichment, and contribution to the overall hydrocarbon-filled rock volume and its ability to flow at producible rates. Mineralogy is key for the geologist and petrophysicist to understand the depositional environment using mineralogical indicators, such as pyrite and siderite compositions. This understanding helps them with derived property predictions on 1D well logs in a basin-scale to per-wellbore-scale integration (Newsham et al. 2019a, b, and c). The compositional analysis of fluids must also be included in all subsurface disciplines to

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While many current technologies are still acceptable, challenges to be tackled include seismic amplitude preservation and complex near-surface conditions.

The focus of the geology, geochemistry, and petrophysics disciplines has shifted toward defining kerogen type, TOC enrichment or leanness, thermal maturity vs. time, and the distribution of organic matter.

Understanding depositional environments using mineralogical indicators is key for geologists and petrophysicists for the prediction of derived properties at the basin scale and their integration into per-wellbore-scale information.

Geomechanical efforts and principles have been completely altered by the horizontal drilling environment, and acoustic and borehole-image-based logging tools are now being used in the opposite intended direction.

Improved understand of the stress state of a given basin and formation will help with enhancing or inhibiting fluid flow by taking into consideration the well orientation and completion impact on the rock column.

Petrophysically, it is now possible to apply thinly bedded analytical solutions by modifying the equations previously used for property interpretation by using measurements made on unconventionals specifically.

map which waters will produce where and why as the industry continues to unravel water production with hydrocarbons in targeted formations where geology and petrophysics quantify both fluid phases in the subsurface; however, the disciplines continue to struggle to predict the production ratios of fluid phases.

Geomechanical efforts and principles have been completely altered by the horizontal drilling environment. Acoustic and borehole-image-based logging tools are now being applied in the opposite orientation for which the tools were designed to function. Fracture presence, type, and distribution are more important than ever, as these inputs can be built into discrete fracture network models, showing the industry how fracture behavior is influenced by wellbore drill path, design, and completion treatments. First-order geomechanical property interpretation from well logs (including gamma ray, bulk density, and sonic by petrophysicists) has indicated that in horizontal environments, the tools need to be pulled apart and every sector of a given acoustic array deciphered to make sure that accurate dynamic Poisson's ratio and Young's modulus values are estimated (Market and Deady 2008; Waters et al. 2011).

The primary focus currently lies with trying to better understand the stress state of a given basin and formation. This understanding helps with enhancing or inhibiting fluid flow by taking into consideration the well orientation and completion impact on the rock column. Defining the minimum and maximum stress states or constraints from derived stress envelopes is critical to influence business production results. It has also become important to model and predict the instantaneous stress imparted by fracturing technology vs. the isotropic or anisotropic natural state of the rock column. Stress profiles and applied modeling are used critically for all horizontal fracturing designs, wellbore placement, and predictions regarding how complex a given fracture design imparted to the rock could end up being.

Petrophysically, it is now possible to apply thinly bedded analytical solutions by modifying the equations previously used for property interpretation by using measurements made on unconventionals specifically (Silva and Bassiouni 1985; Sondergeld et al. 2010). A focus on the interpretation of geomechanical properties, along with pore pressure and fracture gradients, is also important. An understanding of effective vs. absolute vs. steady-state permeability is critical, and guidance for reservoir engineers—from capillary pressure to relative permeability measurements—is needed. Multiple tools and instruments are used to arrive at common data sets for the same parameters, cross-checking the uncertainty in all the competing technologies on the market that are still evolving into best-practice solutions. Cluster-based or machine-learning (ML) rock-typing models are critical to feed simulation efforts to ensure that the permeability of the formation varies appropriately, influencing fluid-flow understanding in 1D single-wellbore modeling to 3D multiwell modeling. A new focus has been placed on advancing and interpreting mobile water vs. bound water (beyond the foundational capillary-free, capillary-bound, and clay-bound definitions) (Nikitin et al. 2017; Pepper et al. 2019). The same applies to the understanding of hydrocarbon-phase mobility related to adsorption and its impact on preferential fluid-flow dynamics.

Advanced workflows for basin modeling, the mobility of fluids, and dynamic fluid-flow modeling and simulation have come a long way and continue to advance. Operational deployment methods for openhole tools in the horizontal logging environment have advanced and continue to improve. Horizontal environmental tool response modeling should continue to be investigated.

Evolving and Future Needs and Expectations

Despite many impressive improvements, seismic prestack amplitude preservation and the ability to use the image for structural and amplitude/amplitude variation with offset in quantitative seismic interpretation remain challenges. Inversion for more-complex reservoir properties, such as anisotropy, also poses difficulties and depends on the reservoir properties (such as thickness). Similarly, imaging under a complex overburden and water-layer multiples and obtaining a better velocity model for imaging using full waveform inversion remain challenging.

The geophysical industry is moving toward increased sampling, and seismic data quality is increasing immensely. The use of seismic for unconventionals is still a work in progress. In general, each piece of substantial seismic technology has taken 5 to 10 years to mature, and we are, in some sense, still in the early development phase, but the technology is maturing for unconventional applications. In unconventionals, there is more demand to estimate properties like pore pressure, anisotropy, and stress that can show very weak sensitivity to seismic data. Rock physics for unconventional reservoirs is still an area of research, and promising methods are being developed. Moreover, the use of fiber optics (FO) data in geophysics is a new frontier that shows great promise. FO data during completion can provide information on aspects such as the most-productive stages, fracture dimensions by stage, optimal usage of pressure, injected fluids and proppants present during each stage, and connectivity between wells. The use of FO during production can help produce a flow profile, and FO can be run at any time during production to see changes in the flow profile.

There has been a significant shift toward advanced analytics, ML, and artificial intelligence (AI) applications geared to the geologist, geophysicist, geochemist, and petrophysicist. ML is expected to substantially help simplify and improve seismic data analysis and interpretation. Much data are available for ML/AI projects, but a significant amount of time and effort are spent on data curing and preprocessing (Akkurt et al. 2018).

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There is more demand in unconventionals to estimate properties like pore pressure, anisotropy, and stress that can show very weak sensitivity to seismic data.

The use of FO data in geophysics shows great promise.

While there has been a significant shift toward the use of advanced analytics, ML, and AI applications, much time and effort are spent on data curing and preprocessing.

Additional advancements have focused on openhole, casedhole, and production logging tools, in addition to laboratory-based methods, instruments, and measurements.

Advancements are needed in the areas of openhole wireline tools, product impacts, and mud logging.

Properly defined methods of calibrating subsurface reservoir characterization models are needed that use techniques and principles rooted in unconventional measurements and applications.

Additional challenges that merit continued focus include laboratory core analysis techniques and workflows, subsurface stress states, and static to dynamic behavior constraints.

Additional advancements have focused on openhole, casedhole, and production logging tools, in addition to laboratory-based methods, instruments, and measurements. There has also been a focus on standard laboratory rock-property measurements to improve the crushed-rock analytical technique that Luffel and Guidry (1989, 1992) developed that has driven unconventional analysis for more than a decade. Techniques that involve a closed retorting quantification method are resulting in saturated volume reporting that is more than 90% accurate when compared to standard techniques, whose accuracy can range from 55 to 85%. The measurements and analyses of organic matter have advanced as a result of programmed pyrolysis multiramp methods, open and closed retort methodology, and scanning electron microscopy (SEM)-based quantification and segmentation volumes (Cheng et al. 2008; Jarvie 2012a, b; Loucks et al. 2012; Loucks and Reed 2014; Durand et al. 2019). The now-commercialized low-temperature hydrous pyrolysis (LTHP) method is revolutionizing the extraction of oil from whole core, resulting in accurate in-situ fluid to rock type characterization.

Multiple tools, including the LTHP method, are focused on and succeeding in production allocation typing through geochemical, petrophysical, geological, and engineering integration. A link between the LTHP techniques and correction methodology for closed retort and fluid-loss quantification for crushed-rock volumes might aid subsurface disciplines in the coming years. Additionally, multiramp or customized programmed pyrolysis worm flows focused on dissecting the volatile hydrocarbon region are helping to link fluid composition type to programmed pyrolysis results and might prove to be highly valuable in helping differentiate mobile vs. immobile hydrocarbon-phase fluids linked to possible recoverable volumes. Reservoir laboratories have designed workflows to physically integrate SEM-based volumes and then model dynamic fluid flow, which shows for a given completion design how the fluids in the pore system of a given rock type will be produced (Camp et al. 2013; Olson 2016). Significant advancements in water- and hydrocarbon-phase mobility vs. immobility have been made and are a continued focus in the technical disciplines.

A continued push is necessary to update and redesign openhole wireline tools so that they can be effectively implemented in high-angle logging environments. Advanced and more-accurate methods, measurements, applied principles, and tests related to production impacts are sorely needed. An area that begs for more science is mud logging—such as in the analysis of cuttings, gas chromatography—especially in unconventional lateral wells where logs are rarely run. Mud logs cut the formation before invasion and/or fracturing and could provide unique information not available from other methods.

The representativeness of laboratory measurements for geological, geophysical, and petrophysical properties is always a concern, especially as they are applied to tight rocks. It is not certain whether in-situ conditions can be duplicated in laboratory tests or how measurements can be scaled to represent the reservoir. Perhaps now is the time to think about robust ways of calibrating models on the basis of reservoir performance. Properly defined methods of calibrating subsurface reservoir characterization models are needed that use techniques and principles rooted in unconventional measurements and applications rather than those from previously defined conventional applications.

Despite the significant advances of the past 10 years, the following shortcomings and challenges deserve continued focus and further advancement as we develop the reservoir characterization of the 21st century:

- Openhole, casedhole, and production logging
- Laboratory core analysis techniques and workflows
- Application of ML and AI
- Resolving scalability
- Linking in-place assessments to recoverable reserves predictions
- Rock and fluid interactions and their influence on quantification
- Subsurface stress states
- Static to dynamic behavior constraints

Critical Knowledge and Experience To Be Preserved and Transferred

Although technologies for reservoir characterization continue to improve, the standard tools and methodologies require significant improvements to accurately measure and assess the quality of modern reservoirs. Reservoir characterization should be performed using an interdisciplinary approach, with attention given to minor fractures and pore-scale flow and primarily based on detailed core analysis. Statistical fracture analysis should be based on adequate structural models that distinguish the different occurring fracture subsets, and these structural models should be supported by adequate multiple-porosity numerical models.

Characterizing and modeling flow in fractured porous media are expected to be continuing challenges. An appropriate approach to reservoir simulation should consider that fractured rock volumes, showing the same permeability values under steady-state conditions, can exhibit substantially different hydraulic behaviors under dynamic conditions.

Integration is a term that is often loosely applied; it can mean different levels of disciplines coming together for a combined subsurface characterization or a model that combines a host of data but does not require more than one scientific discipline to quantify rock and fluid properties. The establishment of a new discipline, such as asset geology or petrophysics, or the use of embedded technical working models could help refocus integration. While the experts and specialists are still necessary in justifying the principle specific needs and focus, the asset can define the role and input of all disciplines and integrate them to improve the description and prediction of rock and fluid-flow behavior in unconventional hydrocarbon-bearing formations.

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Reservoir characterization should be performed using an interdisciplinary approach.

Reservoir simulation should consider that fractured rock volumes under steady-state conditions can be substantially different from those under dynamic conditions.

The essence of integration should be preserved to combine the input from all disciplines and integrate it to improve the description and prediction of rock and fluid-flow behavior.

The role and integration of the input of all disciplines should be defined by the properties and needs of each asset.

Petrophysical and rock physics studies are essential for supporting basin modelers, pore pressure estimates, geomechanics modeling, and completions optimization.

All subsurface characterization roles are critical to the foundation of the oil industry: the evaluation and quantification of hydrocarbons. The petrophysical discipline is applied when taking the acquired data or concepts and constraining the prediction of a given resource volume. Supporting basin modelers, pore pressure estimates, geomechanics modeling, and completions optimization design all require petrophysical and rock physics studies. The subsurface disciplines are unique in trying to combine static subsurface characterization measurements with dynamic wellhead results and build those into a predictive hypothesis and model. All disciplines require support from other specializations to execute science-based applications. Can each discipline help the others more by applying a different lens to the same data sets?

Core Analysis

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Introduction

Core analysis is central to hydrocarbon exploration and production. Core samples extracted from reservoir rocks produce large volumes of data for many types of studies, including petrographical and petrophysical characterizations, reservoir performance prediction, source and seal analysis, and geomechanics, formation damage, geochemistry, and well engineering studies. Core data constitute the "ground truth" (McPhee et al. 2015), and accurate core analysis is essential before any reservoir study is begun.

While there is an established laboratory protocol of core analysis for conventional reservoirs, the link between the laboratory results and reservoir fluid dynamics has yet to be fully established. Furthermore, core analysis for unconventional reservoirs is still in its infancy. This section presents a synopsis of the existing challenges in the current practice and speculates on the path core analysis should take to tackle the current challenges and to meet future industry needs.

History, Background, and Original Concepts

The established core analysis practice is a result of decades-long, extensive research and industry application. [Refer to McPhee et al. (2015) for a discussion on the development of core analysis.] Early work focused mostly on geological description, routine core analysis (RCAL) data gathering, and reservoir performance assessment through simple corefloods using synthetic fluids. Core analysis has since continuously evolved, with new requirements for improved understanding—such as wettability and reservoir recovery mechanisms—and by introducing new technologies such as the simultaneous measurement of capillary pressure and electrical properties using high-pressure porous plates, the recording of fluid-phase pressure during coreflooding, in-situ saturation monitoring, pore-scale visualization, and nuclear magnetic resonance (NMR). Multisensor core scanning now allows the true value of the information held within the core to be realized.

Core analysis is an integrated process. Acquiring core data does not only involve conducting the desired tests on extracted core samples but also requires an extended and detailed process that includes planning a fit-for-purpose study program, low-invasion/sponge/pressure coring, the wellsite handling of cores, transportation, pre-analysis processing, plugging, sample selection, laboratory testing, a data quality check, and a collective analysis of the data from the perspectives of various disciplines (geology, petrophysics, and reservoir engineering). Laboratory testing forms only one part of this multitask process, and failure at any step of this integral process has the potential to invalidate the produced data. Moreover, many technical questions exist regarding how to upscale from the pore to the core scale with the incorporation of subcore-scale heterogeneity.

Many methods/techniques, such as overburden correction and the use of preserved cores vs. restored cores, have been developed to ensure that laboratory core data are representative of the reservoir conditions before entering them into a geological or reservoir model. However, there is still considerable uncertainty in interpretations. The primary sources of uncertainty are the difficulty of conducting tests at in-situ conditions and the alteration of petrophysical properties related to mud invasion and the inevitable chemical and mechanical rock material changes when the core is brought to the surface.

Determining how to enter core data into static and dynamic models has been a challenging task for decades. Recent improvements in reservoir characterization and numerical simulation have made it possible to run simulations on more-complex numerical grids of reservoir-representative heterogeneity. This has inevitably required more-complex data inputs for robust numerical predictions. Initially, a single set of $p_c(S_w)$ and $k_r(S_w)$ or $k_r(S_g)$ curves was deemed sufficient for studying a reservoir; nowadays, multiple curves are required for specific types of reservoir rock. This so-called rock typing allows geoscientists and engineers to characterize reservoirs much more effectively, but the $p_c(S_w)$ and $k_r(S_w)$ or $k_r(S_g)$ curves assigned to each rock type must be delineated in such a way as to represent reservoir recovery mechanisms at different scales for accurate predictions.

The imaging of rock pore space combined with advanced computational methods have resulted in digital core analysis (DCA). Currently, almost all core analysis data could be generated digitally, which allows digital core computations to be made at various scales so that an upscaling from pore to core can be investigated. A complete replacement of laboratory data with DCA data is unlikely and probably undesirable because of the uncertainty in replication. Although proponents of DCA would strongly disagree that the relevance of the digitally derived data has not been

TAKEAWAYS

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Core analysis is an integrated and extended process, and failure at any step has the potential to invalidate the produced data.

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Determining how to enter core data into static and dynamic models has been a challenging task for decades, but recent improvements in reservoir characterization and numerical simulation have made it possible to run simulations on more-complex numerical grids of reservoir-representative heterogeneity.

Currently, almost all core analysis data could be generated digitally (DCA), which allows digital core computations to be made at various scales so that an upscaling from pore to core can be investigated.

Core analysis data for unconventional reservoirs are as important as those for conventional reservoirs, but most of the conventional techniques for RCAL are inapplicable to these reservoirs.

proven, many major operators who themselves advocate for or support DCA still rely on conventional laboratory experiments to provide critical reservoir data.

Core analysis data for unconventional reservoirs (shales, tight formations, coalbed methane, gas hydrates) are as important as those for conventional reservoirs. However, the tight nature of unconventional rock, as well as recovery mechanisms, often render most of the conventional techniques for RCAL inapplicable. The issues of core extraction, core sampling, and reservoir-representative samples are compounded in unconventional rocks by complex geomechanical and surface chemistry properties.

Current Status

Although insufficient characterization of a reservoir is one of the primary causes of uncertainties in oil-in-place and reserves calculations, core acquisition is often assigned a low priority these days. Currently, there exists no standard in the industry regarding how much core data are needed and the minimum/sufficient data volume needed for special core analysis (SCAL). RCAL and SCAL techniques and workflows are well-established, and much literature is available; however, workflows are not standardized, and in some cases, best practices do not reflect modern developments like automatic numerical history matching of experiments and DCA. Similarly, the lack of an established best practice in rock typing influences plug selection and the overall SCAL program. Sample-to-sample variation within a rock type and uncertainties from measurements lead to substantial variation/uncertainty in SCAL data. Numerical data interpretation, including uncertainty modeling, helps manage such uncertainty.

Sample preparation is one of the biggest challenges today in terms of keeping the rock representative of the subsurface conditions (in terms of wettability and mineral integrity). The uncertainty resulting from the difficulty of conducting tests on unaltered samples at in-situ conditions also persists. Although some aqueous- and oil-phase tracers have been used to understand the impact of filtrate invasion on the core state, the phrase "reservoir representative" is still vague. A prime example is wettability, which controls every factor relevant to the

TAKEAWAYS

The industry suffers from a lack of standardization and best practices, which can lead to substantial variation/uncertainty in the data. For example, while RCAL and SCAL techniques and workflows are well-established, the workflows are not standardized, and in some cases, best practices do not reflect modern developments like automatic numerical history matching of experiments and DCA.

Sample preparation is one of the biggest challenges today in terms of keeping the rock representative of the subsurface conditions, and the uncertainty resulting from the difficulty of conducting tests on unaltered samples at in-situ conditions also persists.

Core analysis currently lacks standardized QC/QA methodologies.

New techniques are currently being explored for the rock properties, such as permeability and effective and total porosity, that describe emerging flow mechanisms in unconventional reservoirs.

SCAL in unconventionals also remains primitive, mostly because of the inability to saturate ultratight rocks to known saturation states. NMR could be useful.

Current approaches barely extract a small fraction of the information the core holds, but big-data methods could be useful. In the smart core analysis concept, automated high-resolution core data logging is combined with data analytics and machine learning on all new cores before analysis is performed.

contents of the reservoir and their in-situ transport. In particular, $p_c(S_w)$ and $k_r(S_w)$ curves are significantly affected by wettability. There are standard methods—such as the Amott and the US Bureau of Mines tests—for use in the laboratory, yet the in-situ wettability cannot be accurately assessed. Furthermore, accurate assessments of in-situ wettability raise additional questions regarding how best to restore and/or preserve the in-situ state.

Currently, core analysis lacks standardized quality control/quality assurance (QC/QA) methodologies. SCAL programs are relatively expensive and time consuming, and reservoir core material is often quite limited. Furthermore, inadequate SCAL programs and the misinterpretation of SCAL data can lead to poor forecasts and incorrect business decisions. Numerical data interpretation, including uncertainty modeling, helps manage some of the uncertainty in the analysis, and in rather rare cases, numerical simulations are used for data interpretation and QC, which helps include full physics and link relative permeability and capillary pressure measurements.

New techniques are currently being explored for the rock properties that describe emerging flow mechanisms in unconventional reservoirs. Permeability and effective and total porosity appear to be more challenging to measure for unconventional reservoirs. Even porosity in the traditional sense is not easily defined and measured because of gases that permeate through nanometer-sized pores. Permeability methods in unconventionals definitely require clarification. We have made good use of the crushed-rock method, but it is very empirical. There is still a lack of understanding of permeability "states," such as Klinkenberg, air, gas, and specific brine permeability.

SCAL in unconventionals also remains primitive, mostly because of the inability to saturate ultratight rocks to known saturation states. NMR could be useful. Diffusion, wettability, capillary pressure, and spontaneous imbibition are currently under broad investigation for the development of robust laboratory methodologies. Relative permeability appears to be challenging to measure and could dynamically change as the reservoir ages depending on sorption, geomechanics, and changes in wettability. Commercial laboratories have a limited ability to conduct corefloods on rock samples of submillidarcy permeability. The workload is high for SCAL analysis in unconventionals because measurements need to be conducted at current and future reservoir conditions with advanced equipment and protocols. Enhanced oil recovery (EOR) in unconventionals, which is emerging and will likely have a significant economic impact, also requires sophisticated core analysis practices.

Current approaches barely extract a small fraction of the information the core holds. One method of acquiring big data is the smart core analysis concept, where automated high-resolution core data logging is combined with data analytics and machine learning on all new cores before analysis is performed. The data analytics and machine-learning methods, originally developed outside of the oil and gas industry, are rapid, nondestructive, and noninvasive. Various government and operator-owned core repositories worldwide are currently in the process of or considering creating "digital" clones of the physical cores using multisensor core logging.

Evolving and Future Needs and Expectations

The first and foremost gap in core analysis is the lack of a unified industry standard for a complete and integrated core analysis process. Such a standard would provide a strong base for all stakeholders (commercial labs, operators) and improve data acquisition and quality. Currently, many geoscientists (geomodelers, petrophysicists) and engineers (simulation engineers) in the industry use core analysis data, but only a few are involved in the collection of the data. Given the lack of standards, it remains difficult for those who are not involved in the data collection to understand the process, posing a risk that unrepresentative data will be used in reservoir modeling studies. Standardization should include data interpretation workflows and ensure an honest assessment of experimental errors, data uncertainties with respect to study objectives, and the representativeness of data regarding reservoir conditions.

Like other data, core analysis data are uncertain, and that is often ignored in core data management. The sources of uncertainty in core analysis data range from experimental errors to interpretation uncertainty, and it is not uncommon to see two different measurements from two laboratory vendors for sister core samples (Hensel et al. 1988; Forbes 1997). Commercial laboratories' QC/QA is mostly restricted to the data they are producing, and this level of QC/QA is insufficient for the needs of petrophysicists and reservoir engineers, to calibrate logs and build saturation/height functions and relative permeability curves. QC/QA practices for six sigma approaches (Allen 2006) to core analysis are currently lacking, which stems from the time-consuming nature of SCAL and RCAL methodologies, the difficulty of identifying homogeneous duplicate samples, and a lack of standard and best-practice protocols across vendors. New technologies could be adapted to improve QA practices. An example would be to use 3D-printed rock proxies to create sets of self-similar QA samples and have them tested simultaneously at multiple laboratories.

With few exceptions, the data from core analysis present no more than a "snapshot" of the selected sample. Furthermore, different disciplines may have different views on sampling; while the SCAL expert is interested in rather homogeneous samples, the petrophysicist may be interested in samples relevant for log calibration and interpretation, and the reservoir engineer is interested in the high-permeability zones. As a result, important features of reservoirs (especially carbonates) could remain unexplored by core analysis, which, in turn, restricts the coverage of the relevant recovery mechanisms. An

TAKEAWAYS

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New technologies could be adapted to improve QA practices. An example would be to use 3D-printed rock proxies to create sets of self-similar QA samples and have them tested simultaneously at multiple laboratories.

An objective criteria catalogue for core analysis must be developed and linked to the needs of the disciplines for each development strategy. A "smart" core analysis approach could provide a large data volume that is effectively continuous and enables "intelligent" core sampling for studies of all kinds.

A need exists to increase awareness of the designing and planning of a core analysis study, especially among young engineers.

Because current preserved- and restored-state methodologies have been developed without performing a definitive assessment of the in-situ wetting state, validation is lacking. Unified workflows on sample preparation (cleaning/aging) could be required.

In unconventional rocks, the issues of core extraction and sampling and what constitutes reservoir representative samples are compounded by complex geomechanical and surface chemistry properties.

objective criteria catalogue must be developed and linked to the needs of the disciplines for each development strategy. A "smart" core analysis approach that involves automated core scanning and would precede both RCAL and SCAL could provide a large data volume that is effectively continuous (on a submillimeter scale, in some cases) and enables "intelligent" (informed) core sampling for studies of all kinds.

McPhee et al. (2015) suggest that most legacy core data are not useful because of the lack of a proper fit-for-purpose design. A need exists to increase awareness of the designing and planning of a core analysis study, especially among young engineers. Numerical simulation engineers use the Corey model to produce $k_r(S_w)$ curves and the Brooks-Corey model for $p_c(S_w)$ curves. These models might be acceptable for green fields or marginal fields, but it is essential to produce these curves based on a ground truth—a large volume of high-quality data that properly represents reservoir rock and fluid properties and reservoir recovery mechanisms.

Because current preserved- and restored-state methodologies have been developed without performing a definitive assessment of the in-situ wetting state, validation is lacking. Unified workflows on sample preparation (cleaning/aging) could be required. Moreover, newer developments like digital-rock physics could become a more-useful tool to bracket the uncertainties envelope in $k_r(S_w)$ and $p_c(S_w)$ curves by simulating the sensitivities to interfacial properties, which could enter the reservoir simulation workflow. The proper numerical evaluation also allows for honest uncertainty modeling, delivering a range of $k_r(S_w)$ and $p_c(S_w)$ curves rather than single curves. This is a required input for modern stochastic reservoir modeling; the simultaneous numerical history matching of multiple SCAL data sets should be a best practice, but it is not a common standard.

In unconventional rocks, the issues of core extraction and sampling and what constitutes reservoir-representative samples are compounded

TAKEAWAYS

The few published standards and guidebooks that exist have mostly focused on conventional reservoirs and better represent laboratory perspectives; similar guidelines for unconventional reservoirs (shale, coal) and green fields are needed.

Because core data have been collected for decades, there could be an opportunity to apply data analytics techniques to understand, for example, the patterns for certain rock types. An industry collaboration could add value to this through, for example, building open-source rock catalogs.

Data fusion, upscaling, advanced imaging techniques, and superresolution convolutional neural networks could expand our current capabilities in replicating SCAL data with digital rocks.

Direct numerical simulations and dynamic imaging of pore-scale flows provide new insights into the flow mechanisms that lead to oil mobilization, solubilization, and/or trapping. With the added value of simulations and measured SCAL properties, laboratory coreflooding protocols could be designed to select and refine a given recovery technology.

Uncertainties with respect to the wetting state, interfacial tension, and other factors should be explored, complementing SCAL data. DCA provides a means to explore the parameter space and then direct laboratory studies in more-meaningful directions. Alternatively, DCA can be used to expand (or augment) currently available SCAL or RCAL data to create larger databases for data analytics.

by complex geomechanical and surface chemistry properties. Answers to questions such as whether oil-based or water-based mud is preferred, how pull-out-of-hole schedules should be designed, how invasion affects core analysis, and how laboratory data from different sources should be reconciled are still pending. Similarly, green fields almost always do not have the required data, and analog data are used. Unfortunately, there are no published guidelines regarding how an analog field should be chosen.

Although extensive research has been conducted on core analysis, there are only a few published standards and guidebooks, which have mostly focused on conventional reservoirs and better represent laboratory perspectives (*API RP 40* 1998; McPhee et al. 2015). Guidelines for low-quality chalks have been released (Maas and Springer 2014), but similar published guidelines for other types of unconventional reservoirs (shale, coal) and green fields are lacking.

Considering that core data have been collected for decades, there could be an opportunity to apply data analytics techniques to understand, for example, the patterns for certain rock types using more readily available core analysis data such as RCAL and mercury intrusion capillary pressure data. An industry collaboration could add value to this through, for example, building open-source rock catalogs. This would require the standardization of data formats for interfacing with machine-learning and/or data analytics approaches. Standardization is often the most time-consuming task for big-data analytics, and because legacy data are saved in various formats, an automatic data-mining technique would be required for database generation. Once again, the problem is that data QC must be performed before the data can be used, and that is hard to automate.

To replicate SCAL data, digital rocks must have spatial wetting properties that are representative at the micrometer-length scale, which is still a challenge. In addition, model domains must be large enough to represent subcore heterogeneity while also being of high-enough resolution to capture bottleneck features that influence flow. This is commonly referred to as the resolution vs. field-of-view problem. Data fusion, upscaling, advanced imaging techniques, and superresolution convolutional neural networks could expand our current capabilities. The recent focus on the direct visualization of saturated rock under reservoir conditions has the potential to tackle the wettability challenge. This would provide not only informed surface properties for digital-rock simulations but also insights into defining the term “reservoir-representative core.” A significant gap in DCA is how to accurately represent heterogeneity and wettability because of problems associated with the generation of reservoir-representative cores for SCAL workflows.

DCA also offers great potential for understanding recovery mechanisms at various scales, which could especially add value for unconventional reservoirs and EOR technologies. Direct numerical simulations and dynamic imaging of pore-scale flows provide new insights into the flow mechanisms that lead to oil mobilization, solubilization, and/or trapping. With the added value of simulations and measured SCAL properties, laboratory coreflooding protocols could be designed to select and refine a given recovery technology. Note, however, that large uncertainty in direct core measurements for unconventionals could restrict the validation of DCA computations of core properties.

Uncertainties with respect to the wetting state, interfacial tension, and other factors should be explored, complementing SCAL data. As a result, an uncertainty envelope rather than a defined saturation function could be used in reservoir simulations. In advanced studies, such as EOR corefloods, there are wide ranges of parameters that cannot be tested within a reasonable time frame using standard laboratory techniques. DCA provides a means to explore the parameter space and then direct laboratory studies in more-meaningful directions. Alternatively, DCA can be used to expand (or augment) currently available SCAL or RCAL data to create larger databases for data analytics. Many machine-learning algorithms require a preconditioner before they are trained for a specific task. The preconditioner could be digital-rock data. Then, a specific reservoir could be fine-tuned using existing SCAL and RCAL data.

Standards and best practices, including more-recent developments like the automatic numerical history matching of experiments and DCA, need to be defined; in many cases, SCAL laboratories still rely on classical analytical solutions for data interpretation. This is clearly insufficient because the underlying assumptions are typically not fulfilled in SCAL experiments. For conventional reservoirs, such standards could be based on existing technology. For unconventional reservoirs, the community is far from developing standardization and new technologies, and new terminology could be required.

Critical Knowledge and Experience To Be Preserved and Transferred

The industry lacks common guidelines regarding how to handle legacy data. Every operator has a collection of archived data that needs to be integrated with the new data before any reservoir modeling study can be performed. In many cases, especially for smaller developments, insufficient or no SCAL data are available. In these cases, and for QC, a common SCAL database would be desirable. Such databases exist and are maintained by some companies but are not publicly available. The community would greatly benefit from the creation of a public SCAL database, particularly for decision making, early and small developments, and QC.

TAKEAWAYS

The community would greatly benefit from the creation of a public SCAL database, particularly for decision making, early and small developments, and QC.

Although experience is hard to impart to others, guidelines must be developed to capture, as much as possible, the best legacy-data QC practices of the experts.

The approaches for producing SCAL data using digital-rock simulations also need to be standardized and guided. One approach would be for the industry to provide grand challenges, like those provided for the SPE Comparative Solution Project but for digital rock, to transfer and share experience.

Numerical history matching of SCAL data must be standardized to make the best use of SCAL data.

It would be beneficial to discuss how the hands-on RCAL laboratory education could be redesigned to maximize the benefit for both engineers and the industry. University curricula could be expanded to include SCAL and DCA and/or laboratory approaches for unconventional and conventional rocks.

Moreover, part of legacy data QC is a judgment call by the practitioner based on their direct experience of the methods and equipment in use at the time. Some petrophysical software packages allow SCAL data to be imported and implemented by users with limited knowledge. Such software, however, cannot discriminate between high- and low-quality data. Although experience is hard to impart to others, guidelines must be developed to capture, as much as possible, the best practices of the experts. Unfortunately, there are only a few experts in the industry who can perform QC/QA of legacy core analysis data, especially SCAL data, and most core analysis experts work for major operators or as consultants. In both cases, they must perform the work for which they were employed, usually with project-specific or commercial drivers as the sole priority. There is little time (and no revenue) for such aspirational activities. Because most SCAL studies are performed at commercial laboratories, which have competing commercial interests, achieving the universal adoption of standard practices and monitoring compliance might be challenging—but are also necessary.

The approaches for producing SCAL data using digital-rock simulations also need to be standardized and guided. One approach would be for the industry to provide grand challenges, like those provided for the SPE Comparative Solution Project (Islam and Sepehrnoori 2013) but for digital rock, to transfer and share experience. Various data projects, such as the Digital Rocks Portal (Prodanović et al. 2015), exist. However, high-quality SCAL data should be produced in a laboratory to validate the digitally generated data to advance this field and identify valid/robust approaches.

Numerical history matching of SCAL data must be standardized to make the best use of SCAL data. Proper numerical data interpretation and uncertainty modeling require a good understanding of the experimental procedures and the underlying physical processes. However, numerical SCAL interpretation tools are often proprietary or commercial, which limits their use to very advanced SCAL laboratories. This is a problem, particularly for smaller developments and educational purposes, and the field would benefit greatly if the experience and guidelines could be documented and transferred to younger practitioners.

It is also important to address the problem at its core. RCAL is typically offered in petroleum engineering undergraduate curricula, but that is all the core analysis education a petroleum engineer might receive unless they participate in experimental work during their postgraduate studies. It would be beneficial to discuss how the hands-on laboratory education could be redesigned to maximize the benefit for both engineers and the industry. Although unconventional reservoir evaluation techniques have evolved significantly after the examination of many tens of thousands of feet of core, the information regarding protocols and results is closely held, but these procedures and their advantages and limitations must be disseminated by means of education (e.g., short courses). University curricula could be expanded to include SCAL and DCA and/or laboratory approaches for unconventional and conventional rocks. Programs could be offered as elective courses and/or upskilling courses/workshops for industry professionals.

Pressure Transient Analysis

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TAKEAWAYS

Well analysis was initially limited to the use of oversimplified models and semilog plots.

Log-log type-curve analysis was developed in the 1970s.

The foundations of minifracture (or DFIT) tests were laid in the late 1970s.

Pressure-derivative analysis introduced by Bourdet et al. (1983) significantly improved the identification of flow regimes for straight-line analysis and confidence in type-curve matching.

In the late 1980s and in the 1990s, the development of software enabled computerized PTA and the use of complex analytical and numerical models in interpretations.

The deployment of permanent data measurements created enormous quantities of pressure data.

The introduction of efficient deconvolution algorithms improved the ability to analyze multirate and multiwell tests.

Introduction

The definition and economic viability of a hydrocarbon reservoir strongly depend on the quantity and type of fluids present, quality of the reservoir, and productivity of the wells bringing the fluids to the surface. Although static measurements can provide early estimates, the only direct approach for assessing these characteristics is to analyze the effective fluid flow from the reservoir. The analysis of the effective fluid-flow data, originally called well-test interpretation, is now known as pressure transient analysis (PTA).

In PTA, the pressure response to a production/shut-in sequence imposed at the well is interpreted by matching the field data with an appropriate analytical or simplified numerical model to estimate reservoir properties and completion efficiencies. Historically, the primary flow regime of interest was infinite-acting radial flow (IARF), which provided an estimate of the fluid mobility in the reservoir, the productivity of the well, and some extrapolated pressure. However, methods have evolved to identify and match wellbore behaviors and complex well geometries (generally early time), reservoir heterogeneities, and boundaries (late time).

History, Background, and Original Concepts

Until the late 1950s, well testing was mostly limited to determining reservoir permeability, the skin effect or productivity index, the drainage area, and average reservoir pressure using relatively limited solutions and models by van Everdingen and Hurst (1949), Miller et al. (1950), Horner (1951), and others. Analysis was performed by identifying the IARF portion of the pressure transient data from a straight-line behavior on a semilog plot of pressure vs. a logarithmic time function that may or may not have been corrected for the production history. This approach, known as straight-line analysis, was later extended to other types of flow regimes—such as spherical, linear, and bilinear flow—on the basis of the existence of a linear trend on the Cartesian plots of pressure vs. a specific time function.

New models (e.g., for naturally fractured reservoirs; Barenblatt et al. 1960; Warren and Root 1963; Kazemi 1969) were developed in the 1960s. New solutions and analysis concepts (e.g., wellbore storage and skin type curves) developed throughout the 1970s (Agarwal et al. 1970; Ramey 1970; Earlougher and Kersch 1974) became some of the fundamental analysis tools and laid the foundation for computerized PTA (Abbaszadeh and Kamal 1988; Allain and Horne 1990). The log-log type-curve-matching approach was enhanced by the concept of independent variables, and it became more useful as a reservoir description tool during exploration.

Interest in fracturing tight-gas wells gave rise to fractured-well-test models in the mid-1970s and early 1980s (Gringarten et al. 1974; Cinco L. et al. 1978; Cinco-Ley and Samaniego 1981). The foundations of minifracture tests and diagnostic fracture injection tests (DFITs) were also laid in the late 1970s (Cleary 1979; Nolte 1979).

In the early 1980s, prompted by a revolution in electronic gauges, pressure-derivative analysis (Bourdet et al. 1983) was a significant breakthrough in identifying the flow regimes for straight-line analysis and improving the confidence in type-curve matching due to the simultaneous matching of pressure and pressure-derivative data. Subsequently, the development of computer-generated complex interpretation models offered the opportunity to account for reservoir heterogeneities. In the late 1980s and in the 1990s, software development boosted by personal-computer capabilities led to semiautomatic history matching with complex analytical and numerical models.

Industry embraced horizontal-well technology in the late 1980s. This led to the development of pressure transient models for a wide range of applications of horizontal wells (Clonts and Ramey 1986; Ozkan et al. 1989; Kuchuk et al. 1990; Odeh and Babu 1990; Kuchuk et al. 1991; Ozkan and Raghavan 1991a).

In the 1990s, the fractal reservoir concept was introduced into the PTA of naturally fractured reservoirs (Chang and Yortsos 1990; Acuna et al. 1995), and in the 2000s, anomalous diffusion was introduced as a means of incorporating small-scale heterogeneity into pressure transient models (Raghavan 2011). In the late 1990s and early 2000s, the deployment of permanent data measurements created enormous quantities of pressure data that became natural candidates for PTA, without the need to run specific well or formation tests (Unneland et al. 1998). During the same period, the development of unconventional plays using fractured horizontal wells prompted interest in new PTA models for linear flow in naturally fractured shale-gas and tight-oil plays (El-Banbi and Wattenbarger 1998; Brown et al. 2011; Stalgorova and Mattar 2013).

Effective deconvolution algorithms were also introduced during this period, allowing successive buildups acquired by permanent downhole gauges to be converted into a constant-rate single drawdown with a duration equal to the total well production (von Schroeter et al. 2004; Ilk et al. 2005; Levitan 2005). New deconvolution algorithms also provided new approaches for the PTA of multiwell tests (Levitan 2007).

Current Status

PTA today has little in common with the PTA of the late 1970s because of the tools and technologies now used, such as electronic gauges, permanent measurements, multiphase flowmeters, the latest generations of formation testers, microcomputers, commercial software, analytical and numerical models, and optimization routines.

In terms of the underlying principles and methodology, however, not much has changed. The basic PTA methodology and tools—which were built on a linear diffusion combining Darcy's law, the conservation of mass, and a slightly compressible liquid—might appear oversimplified, but they work reasonably well in the absence of severe nonlinearities and heterogeneities. Pressure/volume/temperature and petrophysical nonlinearities are packaged in pseudofunctions (Al-Hussainy et al. 1966; Raghavan 1976; Agarwal 1979) whenever possible to extend the linear domain. When nonlinear behaviors cannot be neglected or linearized, they are reproduced using numerical models but displayed and matched on the same diagnostic plots on the basis of linear diffusion.

The Bourdet derivative remains the diagnostic and matching function of choice in PTA with a set of specialty plots applied to characteristic flow regimes. However, technical groups or subject-matter experts diverge on some ancillary methodologies, such as deconvolution (Onur et al. 2008). There is general agreement that deconvolution algorithms are useful, especially to add material-balance information and to establish the drainage area for a given well when grouping successive buildups. However, there is disagreement regarding the usability of multiwell deconvolution and the point at which nonlinearities and other system changes will (by definition) invalidate the process (Levitan 2007).

The difficulty of understanding physical diffusion models in tight, unconventional plays has led to a new generation of analytical models (e.g., for fractal reservoirs and anomalous diffusion; Flamenco-López and Camacho-Velázquez 2003; Albinali et al. 2016; Raghavan et al. 2017) and the improved numerical representation of discrete fracture networks (Yu et al. 2018; Artus 2020).

Minifracture or DFIT analysis (Gu et al. 1993; Abousleiman et al. 1994; Mayerhofer et al. 1995; Mayerhofer and Economides 1996; Soliman et al. 2005; Mohamed et al. 2020) is now currently integrated in the PTA workflow and most commercial PTA software. However, the best and most-appropriate methodology(s) to use for minifracture analysis is a contentious issue among subject-

TAKEAWAYS

PTA tools and technologies have advanced, but the underlying principles and methodology remain unchanged.

When nonlinear behaviors cannot be neglected or linearized, they are reproduced using numerical models but matched on the same diagnostic plots on the basis of linear diffusion.

There is disagreement regarding the usefulness of deconvolution, particularly with multiple wells.

A new generation of analytical models and improved numerical representation of discrete fracture networks have emerged.

There is disagreement regarding the best methodology for minifracture analysis.

The use of numerical models varies significantly between operators.

Harmonic testing and impulse tests/closed-chamber tests have gained renewed attention, although concerns remain.

matter experts and major service companies (Hawkes et al. 2018). A discussion is also underway regarding whether we will be able to develop models that can reproduce both production/shut-in and fractures during opening and closure.

The use of numerical models in PTA remains at the discernment of operators. Currently, some operators choose to not use numerical models, some use numerical models only when analytical models have failed, and others consider that a PTA is not complete without a final match with a numerical model.

Harmonic testing (periodic rate sequence, sinusoidal or otherwise, at different frequencies) and impulse tests/closed-chamber tests (instantaneous injection or production of a given volume of fluid controlled by wellbore storage) have gained renewed attention in the past two decades (Fokker et al. 2018; Salina Borello et al. 2019). These tests derive an interpretable periodic signal from measured pressures and offer the advantage of continuing production/injection during the test. However, some concerns currently linger about their interpretability and suitability for reservoir characterization beyond the vicinity of the well.

Evolving and Future Needs and Expectations

The accurate estimation/measurement of flow rates has always been the weak point in PTA. One can expect a continuation in the deployment of permanent measurements: the installation of permanent downhole pressure gauges and fiber-optic equipment and, increasingly, the use of high-frequency multiphase flowmeters. While these flowmeters are, for now, being reserved for high-profile wells, they could become a game changer if one can at last get access to high-frequency, high-quality pressure and rate measurements.

Future improvements in PTA will also come from the use of a combination of measurements. New developments in acquiring pressure, temperature, and multiwell data, multiphase rates, and distributed measurements should lead to new workflows and procedures to enhance continuous appraisal and evergreen models.

Costs, risks, and environmental considerations will continue to limit the number of conventional pressure transient (drillstem) tests to the minimum required. On the other hand, improved data collection by means of a new generation of formation testers and permanent gauges will increase the overlap of the data

TAKEAWAYS

The continued deployment of permanent measurements is expected; the common use of high-frequency multiphase flowmeters could revolutionize pressure and rate measurements.

A combination of measurements—pressure, temperature, and multiwell data, multiphase rates, and distributed measurements—could lead to new workflows, enhancing continuous appraisal and evergreen models.

A new generation of formation testers and permanent gauges will provide supporting data for both standard PTA and formation tests; PTA procedures will help the post-processing of data from new formation testing tools.

If the concerns regarding a short radius of investigation can be addressed, the advantage of having uninterrupted production/injection during harmonic, impulse, and closed-chamber tests would offer more opportunities for PTA.

More-adequate PTA tools are needed for minifracture-test applications in unconventionals.

Automation will likely change the engineer's role, but it is currently unclear how or if automation, AI, and data analytics will ultimately affect PTA methodology.

collected for PTA and formation-test analysis. It is also expected that PTA will take on a larger role in the post-processing of the data acquired using these tools.

If the concerns regarding a short radius of investigation can be addressed, the advantage of having uninterrupted production/injection during harmonic, impulse, and closed-chamber tests would offer more opportunities for PTA. Similarly, there is more to learn and develop regarding injection testing—especially considering that numerical models can readily simulate these operations.

In the area of unconventional PTA, a convergence of concepts/solutions for an industry-standard minifracture analysis methodology is needed. The development of models that can handle both flow and geomechanics should open the door to a unified PTA + minifracture workflow. Additional developments in modeling flow behavior in unconventional reservoirs should be expected and will possibly incorporate nanoscale models of storage and flow behavior (e.g., anomalous diffusion, adsorption, molecular sieving). Last, the industry should be able to reach an agreement regarding what deconvolution algorithms can/cannot and should/should not be expected to achieve.

It is currently unclear how technologies such as automation, data analytics, and artificial intelligence (AI) will affect PTA. Automation is a work that is actively in progress, and actions currently performed directly by an engineer may be taken over by automatic processes that may involve data analytics or AI.

TAKEAWAYS

The foundations of PTA and the importance of models (vs. varying practices and tools) should be emphasized.

Because the availability of a suitable model enables the interpretation, analysts should have the knowledge and experience to couple their interpretations with the model's assumptions.

We must support the training of a new generation of model developers who are equipped with the theoretical and practical foundations and an ability to recognize nonstandard behaviors and complex environments.

We must recognize that nonuniqueness is the natural consequence of the solution of an inverse problem based on an approximate representation of reality by a physical model.

Industry initiatives are currently guiding technology providers to produce microservices that will be functionally equivalent to what engineers do using an interactive software dedicated to the same tasks. One outcome that seems certain is that these technologies will radically change the day-to-day work of an engineer, even if, paradoxically, the PTA methodology itself is unlikely to be affected. Ultimately, the engineer should have the final word on the selection of the physical model.

Critical Knowledge and Experience To Be Preserved and Transferred

Modern software and AI technologies have helped those with limited theoretical backgrounds use PTA for standard cases. However, for more-complex cases, to which PTA is expected to contribute the most, following recipes or using automated interpretation options leads to dramatic failures. To distinguish PTA from empirical curve-matching procedures, the foundations of PTA—which are based on the mechanics of fluid flow in geological porous media—should be preserved and emphasized as an integral part of expertise. It is also essential to recognize that, although PTA uses measured data, it is the availability of a suitable model to represent a given geological context and underlying physical conditions of flow behavior and corresponding diagnostics that enables the interpretation. Therefore, analysts should have the knowledge and experience to couple their interpretations with the model's assumptions.

Some advances in the use of PTA could be possible with improved software capabilities or AI algorithms, but any major improvement will emerge from the development of new models. This requires a new generation of model developers who are equipped with the theoretical and practical foundations and an ability to recognize nonstandard behaviors and complex environments.

As always, the nonuniqueness of PTA results should be accepted not as a weakness but as the natural consequence of the solution of an inverse problem based on an approximate representation of reality by a physical model. Analysts should recognize that the confidence intervals of PTA can only be improved by integrating all available well and reservoir data and understanding the limitations of the model to represent the reality. Most importantly, the value of information from PTA should not be justified on the basis of estimates of individual parameters but in terms of PTA's contribution to the understanding of the well/reservoir system and characterizations of reservoirs.

Rate Transient Analysis

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Introduction

Although the concepts of rate transient analysis (RTA) are founded on the same physical principles, solutions, and models as those of pressure transient analysis (PTA), RTA has evolved over time to claim its own standing as a process for reservoir characterization and diagnosis. In general, the data in RTA are simply used in different ways and typically over different time scales. Unlike PTA, where short-term pressure changes (hours or days) are interpreted, RTA evaluates the entire production history (months to years of data), which requires no shut-ins and causes no loss of production.

Technically, RTA uses the same diagnostic plots and analysis protocols as PTA, which are based on mathematical models of physical phenomena and are often simplified using appropriate assumptions (flow patterns, diffusion type, heterogeneity, phase behavior). Physical parameters are first estimated graphically and then used to initialize and fine-tune more-complex models by means of automated regression algorithms for history matching.

For conventional (high-permeability) reservoirs, RTA often identifies a significant portion of the history as boundary-dominated flow, whereas only a limited number of mostly infinite-acting flow regimes are expected in PTA because of its shorter duration. However, the differences between RTA and PTA lessen in unconventional reservoirs (low-/ultralow-permeability reservoirs) because the entire production history is likely to be in transient flow, and RTA becomes equivalent to a variable-rate PTA.

Unlike the pressure data acquired during a pressure transient test, which are of a higher frequency and have greater accuracy, production data might be roughly estimated from daily records and rarely be of high quality. Moreover, from a strict theoretical viewpoint, RTA leads to a deconvolution problem, which requires both the production rates and the corresponding flowing bottomhole pressures. Although daily rates have become commonly available in the past 10–15 years, flowing bottomhole pressure histories have historically been infrequently available and are often inaccurate. Despite some of its drawbacks, RTA has found more popularity in unconventional reservoir development because of the higher costs and operational concerns associated with PTA.

History, Background, and Original Concepts

It has been suggested (Ilk et al. 2010) that production-data analysis methods are little more than observation-based approaches, and some are essentially rules of thumb. The first systematic efforts to use production data to predict the future performance and ultimate recovery of wells have been credited to the Arps (1945) empirical decline curve approach (exponential, hyperbolic, and harmonic production declines), although Arps (1945) made several references to previous works (Arnold and Anderson 1908; Cutler 1924; Marsh 1928; Allen 1931). The motivation for and development of RTA concepts and procedures evolved from both decline curve analysis (DCA) and PTA between the 1920s and 1970s, but RTA has emerged as a reservoir characterization and well-productivity analysis tool on its own account in the past few decades. In principle, RTA was always known to be a counterpart of PTA, but its potential was not fully explored until the early 2000s.

In 1980, Fetkovich published the original work on production DCA using type curves, and Fetkovich (1980) is considered to be the fundamental reference on the subject. The limitation of Fetkovich's constant-pressure production assumption was overcome in the 1990s (Palacio and Blasingame 1993). Throughout the 1990s, material balance was coupled with the pseudosteady-state flow theory, which provided an analysis/interpretation method for production data on a per-well basis (Palacio and Blasingame 1993; Mattar and McNeil 1995; Agarwal et al. 1999). Efforts to analyze production data combined with pressure led to analysis of the transient productivity index (Crafton 1997; Araya and Ozkan 2002). In 1998, a method based on convolution and DCA was presented for the analysis of bottomhole pressure data acquired with permanent downhole sensors along with rate measurements (Unneland et al. 1998). In the 2000s, guidelines and examples for production data diagnostics for model-based analysis (type curves) were provided, in essence bridging the gap between PTA and RTA in terms of analysis techniques but with a greater emphasis on long-term data as opposed to shorter-term pressure buildups (Mattar and Anderson 2003; Anderson and Mattar 2004; Kabir and Izgec 2006).

TAKEAWAYS

Arps relations (exponential, hyperbolic, and harmonic responses) were the first systematic effort to use production data to predict the future performance and ultimate recovery of wells.

Fetkovich (1980) introduced production DCA using type curves.

The concept of varying production pressure (Palacio and Blasingame 1993) overcame the limitation of Fetkovich's constant-pressure production assumption.

Throughout the 1990s, material balance was coupled with the pseudosteady-state flow theory, which provided an analysis/interpretation method for production data on a per-well basis.

Current Status

Although the standard drawdown and buildup tests are still considered to be the most-reliable transient well tests, cost, safety, and environmental concerns have resulted in the more-common use of RTA since the 2000s. Current RTA theory and procedures, however, are fundamentally the same as those for PTA and do not differ significantly from those used before 2000.

In the past three decades, the industry's shift to horizontal, fractured vertical, and multifractured horizontal wells for field development—particularly in tight and unconventional reservoirs, where extensive testing times are required to obtain analyzable pressure transient data—boosted the use of readily available production data. This move led to the development of new multifractured horizontal well models for unconventional reservoirs in the 2010s (Brown et al. 2011; Stalgorova and Mattar 2013). Developed in parallel with computational capabilities and enhancements in numerical simulation methods, numerical models now complement the suite of analytical models in the RTA toolbox.

The significance of the deconvolution process (and the requirement of bottomhole flowing pressures) to convert the variable-rate, variable-pressure problem to a constant-bottomhole-pressure problem, which is embedded in the pressure normalization of production data and material-balance time, is not well-understood or is overlooked in the usual practice of RTA. The current trend is to fulfill flowing bottomhole pressure requirements by converting the wellhead pressures to bottomhole pressures using wellbore-hydraulics models if the surface pressures are available and then use the pressure-normalized rate (or rate-normalized pressure) against a material-balance time (Palacio and Blasingame 1993; Mattar and McNeil 1995; Agarwal et al. 1999) to analyze the data as if the data were from a constant-pressure production case. However, converting wellhead pressures to bottomhole pressures using approximate wellbore models can introduce artifacts into the data and alter the diagnostics. Moreover, in most cases where the wellhead or bottomhole pressures are not available, the analysis lacks rigor and the rate vs. time data are used without any processing. It must be noted that the practice of estimating or assigning well rates from cumulative production or tank battery records likely compromises the accuracy of RTA. More alarmingly, RTA is sometimes interpreted as DCA, where the importance of underlying physics is overshadowed by an interest in obtaining a fit with a presumed decline trend.

An important shortcoming of current RTA practice is the lack of well-defined procedures for the analysis of multiphase and multiwell production data. The available analytical approaches adapted from the analysis of PTA, such as the total mobility or pseudopressure definitions (Muskat 1937; Perrine 1956; Martin 1959; Raghavan et al. 1999), include assumptions that are not readily justifiable for long transient production periods. The use of numerical

TAKEAWAYS

Current RTA theory and procedures are fundamentally the same as those for PTA.

Numerical models developed in parallel with computational capabilities and enhancements in numerical simulation methods are now part of the RTA toolbox.

The significance of deconvolution is not well-understood or is overlooked in RTA, and approximate procedures are instead used to resolve flowing bottomhole pressure requirements.

RTA is sometimes interpreted as DCA, where the importance of underlying physics is overshadowed by an interest in obtaining a fit with a presumed decline trend.

An important shortcoming of current RTA practice is the lack of well-defined procedures for the analysis of multiphase and multiwell production data.

In the past decade, an interest in an improved representation of flow physics in highly heterogeneous, discontinuous porous media has led to the investigation of anomalous diffusion models.

Although the impact of geomechanics on the performance of unconventional wells has been well-recognized, conventional RTA approaches do not consider geomechanical effects.

models in these cases amounts to history matching using a reservoir simulation study and lessens the benefits of RTA.

In the past decade, an interest in an improved representation of flow physics in highly heterogeneous, discontinuous porous media—such as naturally fractured and tight, unconventional reservoirs—has led to the investigation of anomalous diffusion models (Raghavan and Chen 2017; Raghavan et al. 2017; Albinali et al. 2016; Holy and Ozkan 2016; Chu et al. 2020). These models enable the identification of a greater spectrum of transient flow regimes (under sub-, super-, and normal diffusion conditions) than those recognized by the normal diffusion equation for regularly ordered, linear systems. However, many RTA models for unconventional reservoirs still use normal diffusion and force-fit conventional flow regimes to estimate reservoir properties.

Although the impact of geomechanics on the performance of unconventional wells has been well-recognized, conventional RTA approaches do not consider geomechanical effects. Currently, the only option to account for the effects of geomechanics is to history match the production data with a complex reservoir simulator coupling numerical geomechanics and flow models. However, this approach blurs the distinction between RTA and full numerical reservoir simulation.

Evolving and Future Needs and Expectations

The current capabilities of RTA methodologies have reached the limits of our conventional comprehension of flow in porous media. That is not to say that there is no room for improvement within conventional perceptions, but it appears that most improvements will be in data handling (dealing with large volumes of data, sampling, addressing data noise) and because of better data becoming available with the deployment of high-resolution permanent downhole gauges. It may be plausible to expect the inclusion of other data types (e.g., temperature) with flow rates and pressures. Other important needs include the seamless integration of analysis results into engineering models and consistent multiwell data analysis, instead of the single-well approach prevalent today.

In high-value wells, continuous rate and pressure measurements are acquired at every second to minute throughout the life of the well, offering new interpretation avenues. Bottomhole pressure measurements will likely become increasingly available (especially in unconventional plays), and downhole flow-rate measurements will be standard in deepwater operations, as well as in other operations where extremely large flow rates are experienced.

New instruments provide accurate multiphase production data, but concerns about our ability to analyze multiphase flow tests persist because of the lack of appropriate models and procedures. Similarly, RTA use for multiwell and other complicated well tests, including those performed for complex reservoir geometries and heterogeneities, would benefit from the development of a sound theoretical base.

RTA in unconventional wells remains extremely challenging, primarily because the complexity associated with heterogeneities such as fractures is much greater than that typically considered in traditional RTA models (Chang and Yortsos 1990; Acuna et al. 1995; Camacho-Velazquez et.al. 2008). The potential of anomalous diffusion models to identify flow regimes and accurately interpret them in terms of physical parameters should be actively explored for RTA, particularly for unconventional reservoirs. Additionally, because the bulk-fluid behavior defined by conventional pressure/volume/temperature (PVT) relations is not appropriate to describe phase behavior in nanopore confinement (Firincioglu et al. 2012; Honarpour et al. 2012), confined PVT relations and equations of state will need to be another active area of future development.

Currently, the impact of geomechanics is mostly ignored in standard RTA practices, and the complex numerical simulation approach does not suit the needs of RTA. More-effective approaches linking the RTA methodology with geomechanics need to be developed.

It is also expected that advances in data analytics (DA) and artificial intelligence (AI) applications will positively influence RTA practice. Part of the improvements could come from DA capabilities in dealing with large volumes of permanent-gauge data, denoising, and the identification of outliers, while AI algorithms might empower the automation of RTA for standard applications. The promise of AI to recognize the underlying physical medium and flow process from data could be a great advance for the application of RTA in more-complex conditions, such as multiphase flow and in highly heterogeneous reservoirs. However, these technologies and capabilities will have to be developed elsewhere and be adopted for RTA.

Over the past few decades, the development of analytical and numerical modeling algorithms has led to new classes of semi-automatic advanced interpretation tools that can handle the complexities of real problems, such as nonlinearity (e.g., advanced PVT, pressure-dependent formation properties, phase behavior), petrophysical heterogeneity, and geometrical complexity (boundaries, layering, fractures). These advances in direct modeling call for similar advances in interpretation/analysis steps, data integration, and uncertainty reduction. Because the analyst has to work with a collection of available models

TAKEAWAYS

The remaining advances in RTA will likely revolve around improved measurement using high-resolution permanent downhole gauges and data handling.

The integration of other data types to improve the accuracy and confidence limits of RTA should be anticipated.

Bottomhole pressures will likely become increasingly available, especially in unconventional plays, and downhole flow-rates will be standard in deepwater operations.

Appropriate models and procedures must be developed to address the concerns about our ability to analyze multiphase flow tests.

Anomalous diffusion models and confined PVT relations and equations of state should be active areas of future development.

More-effective approaches linking the RTA methodology with geomechanics need to be developed.

Automation and DA and AI applications are expected to positively influence RTA practices.

The advances in direct modeling call for similar advances in interpretation/analysis steps, data integration, and uncertainty reduction.

Ensuring that the correct flow physics of unconventional reservoirs is used, particularly when Darcy flow alone cannot explain all observations, remains an active issue.

that matches the data but does not necessarily ensure the physical consistency of the interpretation, the interpretation is strongly dependent on the interpreter's proficiency.

Ensuring that the correct flow physics of unconventional reservoirs is used, particularly when Darcy flow alone cannot explain all observations, remains an active issue. Merely adapting our conventional-interpretation models and tools to non-Darcy formations and new types of reservoirs—although this might be sufficient to match the early-time data—does not guarantee that we can build a reliable representation of the reservoir that will lead to the optimal management of the available resource. This is especially true for complex reservoirs where the existence of heterogeneities and nonlinear processes can cause anomalous diffusion.

Critical Knowledge and Experience To Be Preserved and Transferred

Unlike DCA, which predicts future production performance from the extrapolation of an empirical decline relation selected on the basis of the observed production history, RTA is a process that requires an understanding of reservoir flow dynamics, including the underlying physical model, prevailing flow regimes under different well and reservoir conditions, and diagnostic features dictated by the physical properties of the system. Therefore, it is essential that the analyst is well-versed in the foundations of RTA, regardless of the varying practices and applications, and that expertise in RTA is not reduced to learning a software package or following a prescriptive workflow.

The bounds of interpretation resulting from the duality of the physical model and the reality and the nonuniqueness inherent in the solution of the inverse problem (finding the cause from the response) also need to be recognized. In most cases, what distinguishes an experienced analyst is their understanding of the assumptions (physical and mathematical) of the model, applicability of solutions to a given geological context or scenario, options for using alternative models, and when to accept or reject the interpretation. Therefore, a significant portion of RTA experience can be learned by studying the foundations and fundamental concepts.

An important feature of experience in RTA is the ability to recognize/resolve nonstandard behaviors, which requires that the analyst have extensive experience/knowledge of different environments. An analyst might develop this wisdom during their individual professional history,

TAKEAWAYS

It is essential to preserve the foundations of RTA in recognizing reservoir flow dynamics and identifying their corresponding diagnostics. Expertise in RTA should not be reduced to the ability to use a software package or follow a prescriptive workflow.

Being able to understand the assumptions made in model development and the applicability of solutions to a given geological context or scenario is an essential element of RTA expertise that can be learned by studying the foundations and fundamental concepts of fluid flow in porous media.

The experience of RTA experts in recognizing and resolving nonstandard behaviors, which is gained through experience/knowledge of different environments, should be cataloged for transfer to the next generation of analysts.

Understanding the confidence intervals of RTA and having the ability to assess the value of information obtained from the analysis should remain essential to RTA expertise.

but, if documented systematically, some of this wisdom could be converted to learnable knowledge and transferred to the next generation of analysts.

One of the critical questions always associated with acquiring data and running tests is about confidence intervals and the value of information. Aside from the nonuniqueness and geologic uncertainty issues, RTA confidence intervals strongly depend on the quality of the data and the expertise of the analyst. RTA confidence intervals must continue to be constantly improved, through the development and deployment of more-sensitive gauges, increased attention to acquiring the correct data at the required quality, and the appropriate education of analysts. Similarly, the value of information obtained from RTA depends on many variables, such as the economic conditions, company practices, geology and characteristics of the reservoir, and geographic location. It is essential that understanding the confidence intervals of RTA and the value of information obtained from those analyses be considered integral parts of RTA practice and expertise.

Reservoir Engineering

Introduction

Our general perception of fluid flow in porous media, and its associated phenomenological relations such as Darcy's law, inherently relies on the validity of the continuum hypothesis, the existence of a clear separation of scales, and the bulk fluid assumption. These assumptions warrant the perception of flow as bulk fluid transport and permit the volumetric averaging of process variables while imposing certain constraints and assumptions on rock properties and process parameters. Consequently, the conventional characterization of reservoir properties and the quantification of key process variables, as outlined in the Reservoir Characterization section of this green paper, are geared toward meeting the data needs of the models. From an even-broader perspective, reservoir engineering is a hybrid specialty that integrates many concepts in the general realm of the physical sciences, math, and engineering. Over the past 150 years, this integration to meet the specific needs of oil and gas production from reservoirs has created a unique specialty, which now has an impeccable standing on its own. Although no formal partitioning of reservoir engineering into subdisciplines exists, in this section, the subject matter has been divided into six subcategories: fluid flow in porous media, phase behavior and PVT analysis, molecular- and pore-scale modeling, field-scale numerical reservoir simulation, enhanced oil recovery, and well performance.

Fluid Flow in Porous Media

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Introduction

Because of its apparent success in defining a rather-complex transport phenomenon in a relatively simple velocity/pressure-gradient relationship, Darcy's law is highly regarded and has shaped our perception and the modeling of fluid flow in porous media. Darcy flow, however, as described by Darcy's law, is a highly conditional phenomenon that occurs within a small range of low Knudsen numbers (10^{-4} to 10^{-3}) and is mostly satisfied in the ordered networks of micro- to macropores and fractures, meeting the continuum condition. Moreover, the additional assumptions made regarding the rock and fluid properties of a reservoir—mostly for the mathematical convenience of dealing with linear differential equations—further limit the applicability of reservoir flow models. Although the use of numerical models removes some of these limitations by numerically approximating discontinuities caused by large-scale heterogeneity and nonlinearity as a result of pressure- and stress-dependent properties, at smaller scales of heterogeneity and lower flow velocities, a pore-scale and molecular-level modeling approach might be more appropriate.

The pore structures of conventional and unconventional reservoirs have various scales of heterogeneity, which lead to multiple flow mechanisms at different scales. Using the prevailing conventional perceptions restricts our success in modeling and predicting flow and transport in heterogeneous media. In addition, the equations and parameters currently used in reservoir modeling are based on old-fashioned and constrained concepts, which hampers the effective management of challenging fields, such as carbonates, tight sands, and unconventional reservoirs, which are being developed more frequently today.

TAKEAWAYS

Conventional models of fluid flow in porous media are based on Darcy's law, which assumes a continuum, bulk flow, and normal diffusion.

The continuity equation is used to describe advective flow or convective transport and has been extended for multiphase flow.

Muskat (1949) and Hubbert (1956) demonstrated that Darcy's law could be derived from the Navier-Stokes equation of motion of a viscous fluid under the assumptions of no-slip flow in an effective continuum.

Darcy's law assumes that molecular interactions between the fluid and the solid surface are negligible.

Non-Darcy flow at high velocities is given by Forchheimer's expression and Knudsen flow at low velocities.

Single-, dual-, and triple-porosity/-permeability models were developed to capture heterogeneities such as fractures, vugs, and stratification. Geologic heterogeneities such as faults, flow barriers, and layers have usually been represented in terms of boundary conditions.

Well surfaces have typically been modeled as the inner boundary of a flow domain. The sources and sinks representation of wells in the Green's function solutions has enabled the development of a large suite of analytical models.

History, Background, and Original Concepts

Although the microscopic, viscous flow of a Newtonian fluid in a pore network follows the fundamental principles of hydrodynamics, our conventional notion of fluid flow in porous media has been shaped primarily by the homogeneous or bulk-fluid-flow assumption of Darcy's law, which assumes a continuum and normal diffusion. Henry Darcy (Darcy 1856) defined the volumetric flow per unit area in porous media using a linear, empirical relationship with the fluid potential. Combining mass balance, an equation of state, and Darcy's law yields the governing differential equation (continuity equation) for advective flow in porous media. This approach can be extended to include a diffusion/dispersion component, and a pragmatic modeling approach is usually taken for multiphase flow, where Darcy's law is applied to each flowing phase.

Morris Muskat (Muskat 1949) and M. King Hubbert (Hubbert 1956) demonstrated that Darcy's law could be derived from the Navier-Stokes equation of motion of a viscous fluid under the assumptions of no-slip flow in an effective continuum. Also inherent in Darcy's law is the assumption that fluid flow can be defined on a local representative element away from the fluid/solid interface; that is, molecular interactions between the fluid and the solid surface are negligible. Using these assumptions, the motion of fluids in porous media has typically been modeled as the advective transport of a fluid mass with a bulk velocity. The repercussions of this assumption are partly alleviated in multiphase flow modeling by considering the capillary pressure and wettability effects on the relative permeability vs. fluid-phase saturation relationships.

Non-Darcy flow regimes at higher ranges of velocity have been commonly dealt with using the second-order expression proposed by Forchheimer (1901). The other form of non-Darcy flow, which occurs at low velocities and was alluded to at the beginning of this discussion, was not of interest in the oil industry until the recent unconventional resource revolution.

Petrophysical and fluid-phase (saturation) heterogeneity has typically been addressed by local averaging and local equilibria through a stretch of the continuum assumption, which has led to models such as dual-porosity and dual-permeability idealizations of fractured and stratified media. On the other hand, geological heterogeneity—such as faults, flow barriers, and layers—has been represented in terms of boundary conditions. Similarly, well surfaces have typically been considered to be the inner boundary of a punctured flow domain. An exception to this rule is the sources and sinks representation of wells in the Green's function solutions to the diffusion equation (Gringarten and Ramey 1973; Ozkan and Raghavan 1991a, b), which has provided the basis for the subsequent development of a large number of solutions for important problems of interest.

Current Status

A fundamental understanding of the relationship between diffusion/conduction, convection (advection), and reaction in multiphase flow in porous media is essential for reservoir simulation and design and a scaleup of petroleum engineering recovery technologies. Accounting for the coupling between flow and geomechanics (the relation between permeability and stress tensor) is becoming increasingly relevant. Mathematical models describing these processes are obtained by combining the various conservation laws with the constitutive equations for rate processes. These models are typically comprised of partial differential equations (PDEs) and can be nonlinear in nature.

From a theoretical point of view, most dynamic problems are nonlinear phenomena; however, most of them are either treated as linear problems or they are linearized by making some assumptions. Nonlinearity can be caused by nonlinear sources/sinks (reactions), state-dependent physical/thermodynamic properties, the existence of multiphase flow coupled with thermodynamics, complex fluids, or boundary conditions. Coupling the processes at various time/length scales causes an additional complexity, which has led to the development of reduced-order modeling (Balakotaiah et al. 1985; Ratnakar and Balakotaiah 2011), the center manifold approach (Carr 1982; Mercer and Roberts 1990; Balakotaiah et al. 1995), the method of moments (Aris 1956), homogenization theory (Mikelić 2000), volume averaging (Whitaker 2013), and multigrid methods (Wesseling 1992). Because many unresolved scale and data issues still exist, modeling the resulting uncertainties, even at small scales, remains important.

In the case of naturally fractured reservoirs, new formulations have been proposed that consider fractal geometry (Chang and Yortsos 1990; Sahimi and Yortsos 1990; Acuña and Yortsos 1995; Flamenco-López and Camacho-Velázquez 2003; Camacho-Velázquez et al. 2008), which eliminates the assumptions used in the traditional dual-porosity model because the geological/geomechanical origins of most fracture systems do not justify them. In addition, a triple-porosity/dual-permeability formulation has been proposed (Camacho-Velázquez et al. 2005) that considers both a fracture network and a dissolution cavities network.

In the past few decades, nonlocal, memory-dependent descriptions of flow and transport in anomalous diffusion models have gained notable popularity among scientists, engineers, and mathematicians focusing on physical scenarios of crowded systems, such as protein diffusion within cells or diffusion through highly heterogeneous, tight porous media. Unlike conventional perceptions, which focus on the petrophysical heterogeneity of porous media, anomalous diffusion models focus on velocity-field heterogeneity by introducing nonlocal and memory-dependent fluxes (Raghavan 2011, 2012). Anomalous diffusion models are of interest not only because of the heterogeneity caused by varying pore scales and the contrast between matrix and fracture characteristics in unconventional reservoirs (Albinali et al. 2016) but also because of the strong scale dependency of the phase behavior and the complex molecular-level interactions between fluid and solid molecules.

TAKEAWAYS

Accounting for the coupling between flow and geomechanics is becoming more relevant.

Most dynamic problems are nonlinear phenomena; however, most of them are either treated as linear problems or they are linearized.

Because many unresolved scale and data issues still exist, modeling the resulting uncertainties, even at small scales, remains important.

The use of fractal geometry has been proposed for naturally fractured reservoirs.

The anomalous diffusion concept, which focuses on velocity-field heterogeneity by introducing nonlocal and memory-dependent fluxes, offers an option to model production from tight, unconventional reservoirs and understand the mechanisms causing low recovery factors.

There has been an explosion in the use of new, experimental techniques and modeling methods for the study of flow in porous media, but the uptake of these ideas has been modest.

In addition to increasing production from different types of fields—such as unconventionals, deep water, fractured carbonates, and tight sands—new, experimental techniques and modeling methods are being used to study flow in porous media. One example is the 3D imaging of pore spaces of rocks from the nanometer to the centimeter scale and the fluids within them, which enables an understanding of the structures and displacement processes in geological materials (Blunt 2017; Lin et al. 2019). Similarly, the availability and use of public domain codes have enabled the development of modeling methods to predict and interpret processes from the pore scale and greater, which has allowed a better physical understanding of transport and multiphase flow to emerge. Furthermore, the development of two-scale continuum models (Panga et al. 2005) for the reactive transport of Newtonian/non-Newtonian fluids in porous media has enabled the capture of pore-scale physics while significantly speeding up the simulations that lead to accurate and physically consistent numerical solutions.

However, the uptake of these new ideas in the oil industry has been rather modest. Current field-scale simulators still use the traditional models of multiphase flow and transport that were developed more than 60 years ago, while core-analysis measurement techniques have not properly embraced the full potential of accurate 3D imaging.

Evolving and Future Needs and Expectations

The conventional assumptions used to simplify and linearize the diffusion equation are not very useful when the complexity of the system dictates the preservation of nonlinear features of the PDE. Thus, it will be necessary to explore the use of different basic techniques that can be applied or adapted to the study of many nonlinear PDEs of the parabolic type. This could include exploring the use of averaging techniques to develop low-dimensional models that are easier to analyze and capture the essential physics at smaller scales. The representation of such models in a form that retains the physics while speeding up the numerical computations is a necessity.

TAKEAWAYS

Due to the increased complexity of reservoirs, the approximate linearization of mathematical models is not always warranted. To preserve the key nonlinear features of physical systems, simplified and/or multiscale reduced-order modeling and appropriate averaging techniques are needed.

Nontraditional concepts, such as anomalous diffusion, should be considered to enhance the modeling of unconventional flow phenomena caused by heterogeneity, variations in phase behavior, and molecular-level interactions. However, interpreting and quantifying the model's parameters in terms of the characteristics of the system are important.

Molecular models or the data fitting of experimental or field measurements are required to quantify the anomalous diffusion parameters, which represent long-range interactions and the memory dependence of the movement of fluid particles.

High-resolution imaging and pore-scale analysis and modeling need to be combined with conventional special core analysis workflows.

Physics-based modeling should be supplemented by machine-learning techniques to incorporate different sources of information at all scales and to uncover existing patterns.

A broad understanding of transport in porous media should be developed before simplifications are made for specific conditions.

Industry could take note of the theoretical and experimental developments in hydrology, flow in porous media, and chemical engineering.

Interest in anomalous diffusion models raises some questions about the physical interpretation and quantitative characterization of constitutive relations. Unlike permeability or the diffusion coefficient used in the flux relations of normal diffusion, the phenomenological coefficients of anomalous diffusion represent long-range interactions and the memory dependence of the movement of fluid particles. Complex molecular models (Coskuner et al. 2017) or the data fitting of experimental or field measurements (Holy and Ozkan 2016; Chu et al. 2019, 2020) are required to quantify the anomalous diffusion exponent, which delineates the deviation from normal diffusion, and estimate the phenomenological coefficient, which is the counterpart of permeability in Darcy's law. However, an apparent dilemma of this approach is that the understanding and definition of the physical phenomena occur at the molecular level, but the application is inevitably on a much-larger field or simulation scale. This calls for the upscaling of the system properties determined by physical characterization, but with the lack of continuum, conventional volumetric averaging approaches are not warranted.

The industry should consider combining advanced 3D imaging with routine and special core analyses to provide a more-robust and physics-based characterization of rock samples from the pore scale and greater. It is also important to couple physics-based modeling with advanced machine-learning techniques (such as artificial neural networks with deep learning and random forest algorithms) to incorporate different sources of information and to uncover existing data correlations. Such couplings can be used to identify the missing data in predicting those characteristics (such as relative permeability and wettability) that are crucial for studying multiphase flow in porous media and whose estimation can be largely uncertain (Zhao et al. 2019).

From a broader perspective, because of new interests in and applications of reservoir engineering and sciences, it is necessary to incorporate the advances in the understanding of fluid flow into reservoir models and numerical simulators. The current approach is to enforce a simplified model based on a limited perception that is applied to a broad and diverse range of physical flow conditions. Instead, a broad understanding of transport in porous media should be developed first, after which simplifications can be introduced that are based on the scales and internal dynamics of the system. The industry could take note of the

TAKEAWAYS

A broad understanding of flow in porous media must be preserved, and an awareness of the underlying assumptions of conventional and new flow models should be maintained.

The basis for and limitations of upscaling the physical and chemical conditions of pore-scale/molecular-level phenomena to the macroscopic perceptions of flow and the corresponding constitutive relations should be preserved as an essential part of the theory.

The experience and skills to construct mathematical statements of physical flow phenomena in complex porous material should be preserved. Understanding of the correspondence between physical and mathematical descriptions of flow must be emphasized.

An appreciation of the need for and the differences between analytical and numerical approaches for flow modeling should be preserved; having the skills to use both approaches when needed should be encouraged.

Awareness of conventional and contemporary computational methods of fluid-flow models should be maintained.

theoretical and experimental developments in hydrology, flow in porous media, and chemical engineering, most of which have not been published in the specialized petroleum literature.

Critical Knowledge and Experience To Be Preserved and Transferred

Our understanding of flow in porous media has evolved over decades. It is important that expertise and knowledge is retained, with a full appreciation of the different processes occurring at different scales and the assumptions underlying conventional and new flow models. The approximations made in upscaling the physical and chemical conditions of pore-scale/molecular-level phenomena to macroscopic descriptions of flow and the corresponding constitutive relations should be appreciated and understood. Coupled with this, the experience and skills needed to construct mathematical statements of physical flow phenomena in complex porous material should be preserved. In terms of the new concepts and approaches, such as the fractional and fractal approaches and the anomalous diffusion concept, understanding of the correspondence between physical and mathematical descriptions needs to be emphasized.

Even though numerical models are increasing in speed, accuracy, and sophistication, there continues to be a role for analytical approaches, especially as benchmarks to validate simulations and interpret behavior. This is true for both linear and nonlinear processes, and new mathematical developments could provide appropriate tools to obtain solutions for nonlinear problems in particular. Engineers and scientists need to be able to apply both analytical and numerical tools where appropriate.

Phase Behavior and PVT Analysis

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Introduction

Fluid properties are needed during the entire exploration and production life cycle, from exploration to mature asset management to enhanced oil recovery (EOR) and improved oil recovery (IOR). However, as projects mature, the need for pressure/volume/temperature (PVT) data and their integration and interpretation varies depending on reservoir performance. Future needs for fluid-related information are also highly related to the options (such as IOR/EOR and various well treatments) to be used and/or studied. In some cases, additional fluid information obtained during the surveillance/development phase can contain symptomatic information related to initial reservoir conditions (reservoir initialization) and confirm initial assumptions regarding reservoir connectivity.

Ideally, we want to determine and/or predict the phase behavior, transport properties, and interactions of mixtures that contain many hundreds of components. Therefore, we need to address the following questions/challenges for the entire life cycle of a reservoir:

- How can we obtain the correct specimen/sample?
- How do these fluid systems flow, and how do we recover them?
- What are the best practices for recombining a sample to create a representative reservoir fluid?
- What are the minimum data requirements to define a system for a process or processes?
- What is the minimum granularity needed for various workflows and computational techniques?
- How do we confirm an equation of state (EOS) is representative of the actual fluid?
- How does continuous monitoring of the produced-fluid composition help improve our understanding of reservoir fluid behavior, especially during EOR operations (e.g., during gas or solvent injection)?
- How does our improved understanding of phase behavior affect project design and health, safety, security, and environment concerns?
- What is the overall financial impact of the fluids on the integrated workflow?
- If we did not have a physical fluid sample and/or various constraints—including time and import/export restrictions—what would be the realistic alternatives to using a fluid sample?

History, Background, and Original Concepts

Phase equilibria describe the behavior of fluids in nature, including that of the hydrocarbons that we extract from reservoirs. In the petroleum industry, the thermodynamics of phase equilibria address the following question: "Under a given temperature and pressure and mass of components, what are the amounts and composition of the phases that result?" (Kovscek 1996). Understanding reservoir fluids starts with the acquisition of a fluid sample from a reservoir and continues with laboratory measurements to observe and measure basic properties of the fluid, such as fluid composition, formation volume factor, viscosity, and saturation pressure as a function of pressure and temperature. Until approximately the 1960s, using experimental data was the only method to obtain the required basic information, and in many cases, the information was oversimplified because of the limitations of the enabling technologies. For example, it was very common to assume homogeneous fluid distribution (one uniform composition residing in the reservoir).

In terms of multidisciplinary integration, reservoir performance, and fluid management, particularly during the past two decades, measurements in the laboratory domain have become more standardized. This was expected to occur because the measurements themselves became increasingly automated and also because more-commoditized hardware became available in the market. With the advances in desktop computing and/or the accessibility of computational power, industrywide integration efforts became a practical reality. Even though the laboratory measurements have been standardized, collecting hydrocarbon samples that are representative of the reservoir fluids has always been a challenge and influences the reliability of the measurements in representing the reservoir fluid.

The laboratory procedures measuring basic properties in PVT cells to reflect the bulk properties of the fluids are well-established. However, they lack the inclusion of confinement effects and other forces, such as capillary and surface forces, which can dominate the phase equilibrium in the small pores that we encounter in unconventional reservoirs. Phase equilibria are represented mathematically by an EOS, which typically is a cubic equation solved for its roots to determine gas- and liquid-phase properties at the thermodynamic equilibrium and referred to as a flash calculation. EOS parameters are calibrated to match the laboratory measurements. Having a mathematical description of a fluid enables us to incorporate the fluid properties into a compositional flow simulator and help optimize the oil processing and separator design.

Reservoir fluid sampling has not been a standard practice in the oil industry. In the absence of oil samples and proper laboratory measurements, simple API gravity values and the produced gas/oil ratio have been used to characterize the fluids using established correlations. These correlations are empirical and naturally representative of the oil samples from which they were generated. For example, Standing's PVT correlations were generated using 22 different oil/gas mixtures from California oil samples (Standing 1947). A variety of correlations have been developed for different oil samples from different basins. Using these correlations for oils that are completely different in nature and have different compositional fluids is not a great practice but has been necessary because of the lack of data.

TAKEAWAYS

In our industry, thermodynamic principles are applied to phase-equilibrium calculations to determine the amounts and composition of each phase under a given pressure and temperature.

Understanding reservoir fluid properties starts with the collection of reservoir fluid samples. While measurement techniques have improved and been standardized, collecting a representative fluid sample is still a challenge.

EOSes have been used to represent phase behavior. They solve for fluid properties using flash calculations and need to be calibrated to match laboratory measurements.

In the absence of fluid samples and laboratory measurements, simple correlations have been used.

Improved understanding of fluid phase behavior is critical for many EOR applications.

It is challenging to acquire unaltered in-situ samples in unconventionals because of the extremely low fluid mobilities arising from nanodarcy-level permeabilities and potential confinement effects. Our ability to change the fluid phase behavior through gas injection to recover more oil economically from unconventionals depends on the accuracy of our understanding of the complex fluid system in the reservoir.

Current Status

New developments can primarily be categorized into the following six areas: multidisciplinary integration, reservoir performance, and fluid management; artificial intelligence (AI), machine learning (ML), and data-driven predictive analytics, which is covered in the Data Analytics, Artificial Intelligence, and Machine Learning section of this green paper; molecular simulation and the acceleration of flash algorithms; hardware design; unconventional reservoirs (shales and tight/low-permeability gas and oil reservoirs); and complex fluids and reactive systems, including carbon dioxide (CO_2) EOR and CO_2 sequestration.

Multidisciplinary integration has forced the experts in different disciplines to make their processes compatible, especially in the context of providing data from one discipline to another, leading to cooperative action at even the most-basic level. A classic example is how we acquire a fluid sample; we consider the needs of multiple disciplines in advance so that we can share the needed information with each other in a more-coherent manner. That is, all data are generated in a compatible manner from the same batch of fluids.

As outlined in Dindoruk (2019) and Hursan et al. (2016), recent advances in downhole fluid measurements are providing better control of oil-based mud (OBM) contamination and opening possibilities for enhanced geological understanding through refined fieldwide compositional variations. However, the majority of PVT samples are still being analyzed in laboratory settings and tests. The quality of collected samples is affected by poor well conditioning and the invasion of nonreservoir fluids or drilling fluids (OBM) (Altowilib et al. 2019). The ultimate goal is to collect a representative sample.

The concept of molecular simulation is not new, but we finally have the needed computational power at our fingertips, at least for certain types of problems. Although significant progress has been made using simple compounds or pure or binary systems, our problems are still extremely complex (because of variations in pressure, temperature, and the compositions that we encounter in reservoirs). Molecular-dynamics simulations are performed to study the behavior of ensembles of molecules that are hard to investigate using experiments. For example, molecular simulations could help to study the properties of a material that cannot be isolated easily or those of dangerous materials, and it is a good substitute for experiments that require high-temperature and high-pressure environments. Thus, molecular simulations can be used as a complement to experiments (Allen 2004). More effort to understand the impact of the sample size used in the molecular simulations on outcomes should help increase the accuracy of the results and numerical efficiency (Coskuner et al. 2017).

There are two main fronts in advances in hardware design. Much progress has been made in laboratory systems. At the present time, the range of fully automated PVT cells and viscometers reaches pressures of more than 30,000 psia. Some classical visual PVT cells can reach temperatures of 570°F at moderate pressures (3,000 psia). In addition, some visual micromodels have expanded pressure ranges, which now exceed 20,000 psia. Significant progress has been made in two areas: P-T (pressure/temperature) and volume requirements. Progress in both is needed for modern PVT analysis because many deepwater developments are at very high P-T ranges, and acquiring large sample volumes can be quite expensive or risky. Therefore, reducing the required volumes for key measurements has wider implications, from reducing cost and time to widening the envelope for various experiments that might not otherwise be possible.

Current industrial practice for PVT analysis is based on modeling only fluid/fluid interactions while neglecting fluid/solid interactions. This assumption is valid for conventional systems because pore sizes are relatively large compared to the length of the mean free path of fluid molecules. However, fluid/solid interactions play an important role in unconventional reservoirs where pore sizes are comparable to that of the fluid mean free path. For this reason, phase behavior and fluid properties in unconventional reservoirs could deviate significantly from their bulk values (Firincioglu 2013). This is often referred to as the pore proximity effect or the pore confinement effect. Such an effect is more pronounced when the pore size is smaller than 10–15 nm.

For a long time, there was a lack of experimental data to check the validity of the various proposed theoretical models (which provided significantly different results) for these systems. A closer look at Bhatia et al. (2004), Fadaei et al. (2011), Devegowda et al. (2012), Dhanapal et al. (2014), and He et al. (2016) indicates that not all forces are considered in many of these theoretical models. Some of the calibration data that are based on molecular simulation results are not interpreted in the same manner as they were correlated with the series of hydrocarbon compounds.

TAKEAWAYS

In recent years, multidisciplinary integration has forced experts to make their processes compatible.

Recent advances in downhole fluid measurements provide better control of OBM contamination and open possibilities for enhanced geological understanding through detailed fieldwide compositional variations.

Molecular simulations could help to study the properties of a material that cannot be isolated easily or those of dangerous materials, and it is a good substitute for experiments that require challenging conditions.

High-pressure, high-temperature measurements, including the acquisition of visual information through micromodels, represent an advance in hardware design.

Significant progress has been made in the area of phase behavior in nanoconfinement using microfluidic chips, but these measurement techniques are not yet widely used in the industry.

Advanced EOSes—such as PC-SAFT, interaction-of-polar-component modeling, and association models—are being used for complex fluid systems.

Recently, significant progress has been made in the area of phase behavior in nanoconfinement using microfluidic chips (Parsa 2017). This was a reality check for many of the proposed models in the context of determining the phase behavior in the nanopores encountered in unconventionals. Noninvasive measurement techniques are also being developed to improve the accuracy of these measurements (Kamruzzaman et al. 2019).

Because we deal with complex fluids and reactive systems in many reservoirs, decision making involves structural and dynamic reservoir, well, and production facilities modeling. We incorporate fluid behavior into these models by describing the fluids using an EOS. However, because we are encountering increasingly complex fluid systems (in terms of integrated system modeling), we are forced to make use of nonclassical cubic EOS models in our computations. For example, in asphaltene modeling, the PC-SAFT approach is used. Similarly, interaction-of-polar-component modeling is used for the partitioning of CO_2 in water (Venkatraman et al. 2017). Water-partitioning solvents/species, cubic-plus association or association models (Ratnakar et al. 2017), and asymmetrical mixing rules such as Huron-Vidal have found wider acceptance in the industry. In recent years, significant steps have been taken to run flash algorithms faster and even run them on graphics processing units (Shiozawa et al. 2018).

Evolving Needs and Future Expectations

Current and future developments in AI, ML, and data-driven predictive analytics have significant potential to advance the analysis of petroleum fluid properties by means of 1) increasing representative volumes of data, 2) improving the quality and reliability of data, and 3) learning nonintuitive but meaningful data representations. In instances where collected fluid samples are scarce (as a result of, for example, prohibitive costs or unfavorable conditions for acquisition), solutions are needed to characterize reservoir fluids for PVT modeling and their subsequent integration into numerical reservoir models. Statistical and ML techniques that are based on, for example, nonparametric and multivariate regression algorithms [e.g., support vector regression and kernel ridge regression (Onwuchekwa 2018)], functional networks (Baarimah et al. 2015; Oloso 2018) or physics informed/hybrid systems, or superlearners (Yang et al. 2019; Sinha et al. 2020, 2021) can effectively predict PVT data—such as saturation pressure, formation volume factor, mixture density, oil viscosity, and the gas/oil ratio—for missing samples. Moreover, advanced unsupervised learning—

TAKEAWAYS

Current and future developments in AI, ML, and data-driven predictive analytics have significant potential to advance the analysis of fluid properties.

Data-driven or physics-informed data-driven modeling could represent a viable alternative to empirically derived correlations to predict reservoir fluid properties.

An ongoing effort is the industrywide acceleration of flash algorithms and various relevant techniques that are coupled with conventional reservoir simulators, yet this task is becoming more challenging as the fluids and models become more complex.

Conventional PVT models are inadequate for predicting fluid behavior in nanometer-size pores. For fluid analysis in such systems, the use of miniaturization and microfluidics/nanofluidics, and the need for extremely small sensors and transducers are increasing steadily.

Significant progress is also being made in the area of fluid sampling.

Some miniaturization efforts and scaled-down lab-on-a-chip-type initiatives could lead to the bringing of the laboratory to the sandface.

such as multidimensional scaling or self-organizing maps (Dossary et al. 2016)—can be used to identify regionalized and compartmentalized reservoir areas on the basis of PVT signatures and/or (dis)similarities in fluid attributes. Data quality and overfitting are still part of the key challenges for the application of ML to correlation development (Yang et al. 2019).

While empirically derived correlations, such as EOSes, have been routinely used to predict reservoir fluid properties, data-driven modeling could represent a viable alternative. For example, a family of ML models can be trained with a resemblance of multivariate sample attributes to predict and optimize decontamination techniques, such as well conditioning, near-wellbore cleanup, skimming, and subtraction. Various mainstream multivariate regression algorithms can perform such tasks, including collaborative filtering (Onwuchekwa 2018). However, the most-significant accomplishment, which has been driven by the developments in deep learning on large-scale networks and graphs, has been the incorporation of meaningful representations of PVT data in integrated reservoir studies and reservoir simulation modeling. When reservoir simulation models are abstracted by networks and/or graphs, the field-scale representations and embeddings of PVT properties associated with network nodes could be learned by studying network connectivity, node adjacency, and network dynamics in a fraction of the time currently required to predict reservoir fluid movement using reservoir simulators.

An ongoing effort is the industrywide acceleration of flash algorithms and various relevant techniques that are coupled with conventional reservoir simulators. Although progress has been somewhat slow and steady, it remains an important endeavor because the problems that are being worked on are becoming increasingly challenging (more grids, more components, more geological complexity, and a desire for real-time decision systems). Significant progress is also being made in the area of fluid sampling, including sampling at various depths at one time and measuring selected in-situ fluid properties in real time. Most in-situ measurements are performed using indirect proxy measurements, such as through the use of optical techniques (e.g., downhole fluid analysis by means of optical density measurements), rather than through an actual pressure/volume expansion/compression implementation. Some miniaturization efforts and scaled-down lab-on-a-chip-type initiatives could lead to the bringing of the laboratory to the sandface (Fadaie et al. 2011; Xu et al. 2017).

Conventional PVT models tend to be inadequate for predicting fluid behavior under the influence of pore proximity for nanometer-size pores. Clearly, greater precision and extremely small sensors and pressure-control devices are needed for such measurements. The role of miniaturization and microfluidics and nanofluidics in fluid analysis is increasing steadily. The need to modify flash algorithms and EOSes for confinement has been demonstrated in many papers, but the industry has not yet adopted these improvements in its applications. Flash algorithms and EOS characterizations should be modified to reflect the other forces present in confinement. Filtration is another complication observed in experimental work for nanoporous media. Preferential flow of smaller components through nanoporous rocks should also be understood and factored into the fluid composition distribution in the reservoir and produced-fluid stream. EOR is a method of accessing the oil left behind in unconventional reservoirs. Thus far, gas-injection huff 'n' puff is the only EOR technique that has been proven to work for these reservoirs. Reservoir fluid property changes—such as an increase in formation volume factor as the gas dissolves in oil, the evaporation of lighter-oil components into the gas changing the liquid content of the gas, and extractive power/miscibility—are the reasons for the improved oil recovery. The industry should invest in measurement techniques specifically for unconventional reservoirs that can address how the gas is interacting with oil in these nanoporous rocks and how we can optimize EOR accordingly.

Critical Knowledge and Experience To Be Preserved and Transferred

As experienced professionals leave the industry, especially during downturns, our industry loses skills that are critical to the success of oil and gas exploration and production, which means that we reinvent the wheel after each downturn and we waste resources. With the advancements in computing, new engineers tend to be very good at calculating results yet lack fundamental understanding of the underlying physics to interpret them.

Some academic knowledge is critical to understand the impact of fluid characteristics, such as formation volume factor and the gas/oil ratio, on production performance. For example, greater formation volume factors provide more energy and more hydrocarbon production. When a reservoir reaches the saturation pressure, gas comes out of the solution, reducing the energy of the oil. Meanwhile, because gas mobility is much greater than that of oil, free-gas production also reduces the oil production. Developing such fundamental understanding of the dynamics of flow in a reservoir, which combines physics with practical knowledge, will help engineers assign a value to the fluid data and associated information and could help fluid characterization become a necessity rather than a scientific exercise.

When experimental data will be used to create an EOS for the mathematical representation of the fluid behavior, the meaning of EOS parameters such as critical pressure and temperature should be well-understood. During the regression of these parameters, merging nonphysical parameter values to obtain a match with the experimental values should be prevented. Proper component lumping for different fluid systems is also essential knowledge to obtain an EOS with a practical number of components. Information on how to use different software packages to develop EOS models and when to use other approaches (in combination or

TAKEAWAYS

New engineers must have a fundamental understanding of the underlying physics to interpret their calculated results.

The development of a fundamental understanding of fluid behavior that combines knowledge of physics with the dynamics of flow and well performance will increase appreciation of the importance of fluid data.

Understanding EOSes and EOS parameters, data-driven models, and correlations and having an ability to switch between various approaches are necessary skills to master.

A multidisciplinary approach to define compartmentalization and how to use fluid data in that context is required.

Physical understanding of how the P-T diagram shifts and how PVT properties change during gas injection, coupled with the concepts of miscibility and the dynamics of the mechanisms that enable improved oil production, is also needed.

Graduating students should understand the implications of fluid characterization and how it can be used in petroleum engineering applications in a multidisciplinary fashion.

Understanding the role of fluids and treating the mineral/mineral surfaces as part of the phases can lead to a better definition of wettability, which has large implications, from EOR to carbon capture, utilization, and storage.

Students should understand the bulk nature of typical PVT measurements and the changes in fluid behavior in confinement.

alone), such as correlations and data-driven models, is also critical. The uncertainties, assumptions, and limitations for each approach used should also be well-understood.

Defining different fluid compartments or equilibrium/disequilibrium grading using fluid characteristics is an important multidisciplinary application of fluid behavior. In this case, fluid characteristics are combined with information from structural geology, petrophysics, geochemistry, stratigraphy, and production to determine the compartmentalization in the field.

One critical piece of information is how the phase behavior changes in the presence of solvents such as CO_2 or hydrocarbon gases during EOR or CO_2 storage. Physical understanding of how the P-T diagram shifts and how PVT properties change during gas injection is essential to decipher the mechanisms that enable improved oil production.

Understanding the implications of fluid characterization and its multidisciplinary use in petroleum engineering applications—such as in facility design, flow assurance, supporting some of the geological realizations in combination with pressure transient analysis and reservoir modeling—would be a big advantage for graduating students. Understanding the role of fluids and treating the mineral/mineral surfaces as part of the phases could lead to a better explanation for wettability, which has large implications, from EOR to carbon capture, utilization, and storage. For unconventional plays, students should understand the bulk nature of typical PVT measurements and the fundamentals of changes in fluid behavior in confinement.

Molecular- and Pore-Scale Modeling

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Introduction

Reservoir simulations have traditionally modeled macroscopic flow phenomena, which are observable at the continuum scale, in conventional reservoirs with micron-sized pore and pore-throat structures. The parameters used in these simulations are typically averages of pore-scale properties. Flash calculations yield phase compositions and volumes that are identical to those obtained in the absence of porous media.

In unconventional reservoirs, the effects of interfacial tension and the contact angle on multiphase flow become more pronounced. Flash calculations yield different compositions and volumes in the presence of interface curvature. As the pore size shrinks toward the nanoscale, pore structures and fluid compositions become more complex and discontinuous; flow and transport mechanisms cannot be modeled under the continuum assumption, and macroscopic transport models need to consider the pore-space constraints. The solids also significantly influence the state of the fluids in nanoscale pores. In the smallest pores, distinct fluid phases disappear, and fluids transition into molecular mixtures.

Molecular- and pore-scale models and simulations are used to characterize the state of the fluids, fluid/surface interactions, flow and transport in pores, and the responses of fluids and porous media to stress, electric potential, and nuclear magnetic resonance (NMR). They complement petrophysical measurements of capillary pressure, relative permeability, geomechanics, resistivity, and NMR.

Molecular modeling is used to understand the internal structure of fluids at the molecular level that results from fluid/fluid and fluid/wall interactions in a pore. Because of computational limitations, these studies are often limited to fluids in single nanopores. An important element of digital core analysis (DCA), pore-scale modeling is a numerical approach used to understand the mechanics of fluid/fluid and fluid/solid interactions, typically at a scale that encompasses many pores.

In unconventional tight-oil and -gas reservoirs, as fluid/surface interactions become important and the pore size begins to reach the limit of the fluid continuum, molecular dynamics becomes the appropriate computational approach.

History, Background, and Original Concepts

Two pore-scale modeling approaches are used for flow and transport in porous media. Direct numerical simulation (DNS), not to be confused with DNS in turbulent flow, directly uses a representation of the pore space as the simulation grid. Different approaches can be used to simulate the same physics. While direct simulation is conceptually straightforward, it is computationally expensive, particularly for complex porous media with pore sizes that vary by many orders of magnitude.

The second approach, called pore-network modeling (PNM), was first introduced by Fatt (Fatt 1956a, b, and c) and idealizes the complex network of connected pore bodies and throats as simplified elements and treats fluids in these elements as continua. PNM uses networks extracted from a representation of the 3D pore space that have assigned rules to approximate flow and transport in porous media (Celia et al. 1995; Berkowitz and Ewing 1998; Blunt 2001; Joekar-Niasar and Hassanizadeh 2012). These models have recently grown in sophistication and can now handle a variety of different physical conditions and processes.

For molecular modeling, two numerical methods are used: molecular dynamics (MD) simulation and Monte Carlo (MC) simulation. MD simulation simultaneously computes the trajectories of all the fluid molecules in a pore by numerically solving Newton's equations of motion on the basis of the forces present among the fluid molecules and atoms that make up the pore walls and their potential energies. Because the simulation involves a many-body problem, rather than simple two-body problems, these simulations are limited to relatively simple single-pore models, and they often capture the dynamic behavior for only a short time (< 1 nanosecond). MC methods, on the other hand, rely on equilibrium statistical mechanics. These methods generate an ensemble of molecules in the pore according to the Boltzmann distribution rather than their dynamic behavior. MC methods have been used to study the storage of hydrocarbon fluids under thermodynamic equilibrium (Bui and Akkutlu 2017), whereas MD simulations have been used for both storage and transport studies (Ambrose et al. 2012; Riewchotisakul and Akkutlu 2016).

In many cases when constructing a digital core, pore sizes range over several orders of magnitude, and despite advances in imaging, it is not possible to generate a fully resolved image of a rock. As a result, a suitable multiscale model that couples different scales in a realistic manner and allows for the reproduction of realistic results needs to be used (Bultreys et al. 2015; Nie et al. 2015; Suhrer et al. 2020). Features that are not geometrically resolved on the

TAKEAWAYS

DNS, one of two pore-scale modeling approaches, directly uses a representation of the pore space as the simulation grid; it is straightforward but computationally expensive.

The second approach for pore-scale modeling is PNM, which idealizes the complex network of connected pore bodies and throats as simplified elements and treats fluids in these elements as continua.

MD simulation is one of two numerical methods used for molecular modeling, and it is limited to a relatively simple single-pore model that often captures the dynamic behavior for only a short time.

The second method used for molecular modeling is MC simulation, which generates an ensemble of molecules in the pore according to the Boltzmann distribution rather than their dynamic behavior.

When constructing digital cores, a suitable multiscale model that couples different scales in a realistic manner and allows for the reproduction of realistic results needs to be used.

Determining from where to take rock samples, the resolution at which to image them, and a REV for single-phase and multiphase problems are necessary tasks in building a digital-rock model.

finest image scale have to be modeled, including pore-wall roughness, the occurrence of oil/water films, advancing and receding contact angles, and other nanoscale effects. Another important task is to transfer the dominant physical effects that are present on certain scales to other scales using appropriate computational models.

The first task in obtaining a 3D image of a rock (a digital-rock model) is to determine from where to take rock samples and the resolution at which to image them to make the simulations relevant. One might start with logs, whole core, plugs, sidewall core plugs, rock fragments, or cuttings. Software and tools, which are often based on machine-learning approaches, are available for clustering and selecting samples from log data and texture and fabrics classification. Another important task for building relevant models is to determine a representative elementary volume (REV) for single-phase (Hilfer 1992; Biswal et al. 1998; Saxena et al. 2018) and multiphase problems (Mu et al. 2016). Different properties (e.g., porosity, permeability, conductivity, capillary pressure, relative permeability) also require different REV sizes.

TAKEAWAYS

As the production of hydrocarbon resources becomes more challenging, there will be a pressing need to refine our understanding of fluids in pores and our interpretation of petrophysical measurements.

Direct simulations of fluid flow governed by the Navier-Stokes and Brinkman equations can now be carried out straightforwardly using established computational fluid dynamics methods.

Molecular simulations have been carried out in single pores and in 3D pore models to obtain insights into pure and multicomponent fluid behavior under nanoconfinement.

Current Status

Over the past 20 years, the ability to perform simulations below the porous-media continuum scale has greatly advanced as a result of developments in imaging technologies, simulation methods, and high-performance computing. We expect that as the production of the remaining conventional and new unconventional hydrocarbon resources becomes more challenging, there will be a pressing need to refine our understanding of fluids in pores and our interpretation of petrophysical measurements. Digital core and modeling will be important tools for meeting such needs.

Direct simulations of fluid flow governed by the Navier-Stokes and Brinkman equations can now be carried out straightforwardly using established computational fluid dynamics methods. Single-phase permeability values derived from such simulations are now well-accepted, provided that the pore spaces used in such simulations are representative and well-resolved; single-phase conductivity values based on the solution of the diffusion equation can also be obtained in a reliable manner. Zhao et al. (2019), which used an artificial porous medium and included extensive experimental data for pore-scale two-phase flow in different regimes and numerical simulations, has been very helpful in judging the efficiency of different numerical approaches. Many imaged experimental saturations under various conditions and in a variety of sandstones and carbonates have been published at the Digital Rocks Portal (Prodanović et al. 2015).

Molecular simulations have been carried out in single pores and in 3D pore models to obtain insights into pure and multicomponent fluid behavior under nanoconfinement (Falk et al. 2015; Bui and Akkutlu 2017; Zhu et al. 2020; Coskuner et al. 2021). These simulations highlight large compositional variations across the width of a nanochannel or the diameter of a nanopore, which can cause pore-size-dependent average density and viscosity and the separation of components during transport in unconventional reservoirs.

Evolving and Future Needs and Expectations

Although much progress has been made, many gaps still need to be filled. A fundamental challenge is the dynamic incorporation of subscale phenomena, which still requires multiscale integration. There is also a need to combine well-designed experiments and digital simulations to obtain effective parameters. Ultimately, we want to build multiscale features of fluids and porous media into common PNM or DNS frameworks and then use them to efficiently upscale to assist core-scale analysis and reservoir simulations.

Specific methods have their challenges, though. Using DNS for multiphase flow or complex fluids (such as foams or particulate flows; Mirabolghasemi et al. 2015), for instance, is notably difficult. Molecular-scale simulation of complex fluids, including complex hydrocarbon compositions and minerals, is another challenge that has not been adequately addressed. Our ability to predict multicomponent fluid properties and phase behavior as functions of pore size using equations of state is limited because fluid behavior is sensitive to the surface chemistry of the walls. Developing realistic atomistic kerogen models is costly, and a clear methodological path toward predictive modeling is lacking. Attempts to mimic organic maturation and kerogen pore network generation have been made recently (Bui et al. 2018), but modeling efforts are in their infancy.

Accelerating multiphase simulations for larger systems is very important for commercial applications, but building high-fidelity and highly optimized solvers will require a considerable investment of resources and manpower. The thickness of fluid/fluid interfaces is generally on the order of a few nanometers, but many DNS methods use diffuse interfaces that are much thicker than nanometers, leading to poorly resolved multiphase flows. Interface thickness is a significant source of error in these simulations, and it should be controlled so that it does not affect the outcome of the simulations. However, if diffuse-interface methods

TAKEAWAYS

Dynamic incorporation of subscale phenomena, which requires multiscale integration, is a challenge. Combining experiments and digital simulations to obtain effective parameters is also a need.

Multiscale features of fluids and porous media must be characterized, built into PNM or DNS frameworks, and upscaled to assist core-scale analysis and reservoir simulations.

Molecular-scale characterization of the phase behavior and transport properties of complex nanoconfined fluids, and a clear methodological path toward predictive modeling using equations of state as a function of pore size are needed.

Accelerating multiphase simulations for large systems is important for commercial applications but building high-fidelity and highly optimized solvers will require a considerable investment.

Direct numerical methods for fluid flow should be expanded to include three-phase flow and complex/non-Newtonian fluids.

Multiphase flow models that can account for multiscale features on all scales and the factors that affect the composition and mobility of interfaces are needed.

Modeling pore-scale geomechanics is very challenging, but the insights gained using modeling and simulation on the pore scale could potentially advance the field.

Molecular-scale studies are needed to explore the effect of confinement on the phase behavior of fluids.

Molecular- and pore-scale data need to be properly upscaled to core and reservoir scales.

could reproduce the widths and density variations of real interfaces, they could become very useful for simulations of nanoscale multiphase systems (Kikkinides et al. 2008; Huang et al. 2019).

The capabilities of numerical methods should be expanded to include three-phase flow and complex and non-Newtonian fluids. Reservoirs simultaneously saturated by oil, gas, and water are very common. However, there have been few direct simulations of three-phase flow in porous media (Mohammadmoradi and Kantzas 2017; Helland et al. 2019). Similarly, despite the widespread use of polymers, foams, and microemulsions, direct simulations that can capture the non-Newtonian characteristics of these flows have also been very limited (De et al. 2017; Ataei et al. 2021).

Multiphase fluid dynamics in porous media are very sensitive to factors that affect the composition and mobility of interfaces. Multiscale features—such as adsorbed surfactants on fluid/fluid surfaces, adsorbed molecules on fluid/solid surfaces, and the roughness and wettability of solid surfaces—can affect multiphase flow in nontrivial ways, and multiphase flow models that can take these factors into consideration on all scales are needed. Most, if not all, pore-scale direct simulations of fluid flow assume velocity continuity at fluid/solid interfaces and velocity/stress continuity at fluid/fluid interfaces. These assumptions, however, have been challenged by molecular simulations and experiments. For example, there is now ample evidence that fluid transport can possess significant surface slip (Fathi et al. 2012). It is also well-recognized that interfaces covered by amphiphiles can have their own viscosities and elasticities and thus break velocity/stress continuity (Fuller and Vermant 2012).

Modeling pore-scale geomechanics to actually run predictions of triaxial tests and rock failure is an extreme challenge (Chen et al. 2020; Sun et al. 2020). This area has not received as much attention as transport problems have. Nevertheless, rock mechanics is often ad hoc, but its importance to unconventional reservoir development is ever increasing, and the insights gained using modeling and simulation on the pore scale could potentially advance the field.

More molecular-scale studies are needed to explore the influences of nanoconfinement on the phase behavior of the fluids (Didar and Akkutlu 2013). A produced-gas composition, when redistributed into the nanopores, under reservoir pressure and temperature, creates capillary condensation as a result of nanoconfinement (Baek and Akkutlu 2019). During pressure depletion, nanoconfined oil shows delayed vaporization (lower bubblepoint pressure) because of its pore-size-dependent composition. All of these nanoscale observations of the fluids are sensitive to the chemistry of the pore walls (Cristancho-Albarracin et al. 2017). Whether the fluid is interacting with a clay surface vs. an organic material with a certain level of thermal maturity influences the observations significantly. The dependence of the fluid behavior on the surface chemistry means that predictions of molecular simulations will vary significantly with the pore model used; hence, although the simulations produce results that are useful for fundamental studies, upscaling needs to consider the heterogeneity in fluid compositions and pore-surface chemistry.

Pore-scale findings must also be linked to core-scale analysis and, ultimately, reservoir dynamics. Because most pore-scale simulations cannot reach the size of a fraction of a core (except for PNM), multiscale characterizations and upscaling by means of multiphysics continuum-scale simulations are needed to examine if molecular- and pore-scale findings can be clearly manifested at the core level and in the field. Therefore, pore- and molecular-scale models need to be verified and calibrated by physical experiments at different length scales.

Critical Knowledge and Experience To Be Preserved and Transferred

Molecular- and pore-scale modeling techniques are tools that connect images of rocks to their petrophysical properties. While upscaling molecular- and pore-scale physics to core and reservoir scales remains a challenge, with advances in imaging and computation, much knowledge and experience have been gained. It is essential that the experience is converted to knowledge and documented for the use of the future generations.

Much of the fundamental knowledge and expertise on molecular- and pore-scale modeling—such as the physics and methodology of imaging, the design and optimization of computational fluid dynamics, and molecular physics methods—have already been developed and documented in other disciplines. The available information from the other disciplines should be accessed through the literature, and the relevant learnings should be reviewed and transferred to petroleum engineering and the geosciences. For applications in the oil and gas industry, it is important to maintain the specific knowledge and expertise regarding: 1) the multiscale features of reservoir rocks and characterization methods; 2) computational methods and results for fluid states and the petrophysical properties of rocks; 3) the physics of and methodology for multiphase flows, particularly the development and use of network models because they have proven to offer superior upscaling potential while maintaining flexibility to accommodate new and complex physics; and 4) the state and rheology of complex molecular mixtures in small pores subjected to strong surface forces.

In addition, data sets that contain both experimental measurements and simulation for accurate knowledge integration need to be maintained. Because data sets that connect experiments and DCA are large and continue to increase in size, they are at a greater danger of being lost during an academic and industry transition than software is. Specialized data portals—such as the Energy Data eXchange (National Energy Technology Laboratory 2011), Digital Rocks Portal (Prodanović et al. 2015), and SPE Data Repository (Society of Petroleum Engineers 2021)—are emerging, but the community needs to support their upkeep to prevent critical data loss.

TAKEAWAYS

The knowledge and experience regarding the upscaling of molecular- and pore-scale physics to core and reservoir scales should be documented for the use of future generations.

Knowledge and experience regarding pore-scale modeling and associated computational methods developed outside the petroleum engineering discipline should be accessed and transferred over.

The multiscale features of reservoir rocks and appropriate characterization methods should be recognized and emphasized.

Computational methods and results for fluid states and the petrophysical properties of rocks should be documented.

The physics of multiphase flow should be well-understood, and the development and use of network models for multiphase flow should be encouraged for their upscaling potential.

The state and rheology of complex molecular mixtures in small pores subject to strong surface forces in unconventional reservoirs should be well-documented.

The upkeep and maintenance of important data sets must be supported.

Field-Scale Numerical Reservoir Simulation

Contributors

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Introduction

Numerical reservoir flow simulators are thermodynamically consistent models of the transport of multiple fluid phases and their components in a heterogeneous hydrocarbon-bearing reservoir that is subject to regulatory considerations and the constraints of the recovery strategy, surface/subsurface operations, market demand, and the investment strategy. Reservoir flow simulators are routinely used by the industry to verify and refine reservoir characterization, predict the dynamics of the reservoir under various operating conditions, estimate recovery profiles, identify optimal development plans, quantify surface and subsurface uncertainties, and monitor field operations. Numerous studies have reported many successful applications of reservoir flow simulation technologies and demonstrated their benefits. However, it is widely agreed that uncertainties can exist in predictions, and it should be noted that these uncertainties result from our limited knowledge of the initial/boundary conditions of reservoirs and, perhaps more importantly, reservoir geology.

History, Background, and Original Concepts

A number of companies recognized the usefulness of numerical reservoir simulators in the late 1950s, with first versions of usable reservoir simulators emerging in the early 1960s. Since then, continuous development has made numerical reservoir simulators invaluable tools in the modern management of hydrocarbon resources.

Two types of models predate numerical reservoir simulators: electric analog models and scaled physical (fluid flow) models. Electric analog models were made obsolete because the same problems can be solved more efficiently with a numerical reservoir simulator. Scaled physical models (such as micromodels, Hele-Shaw cells, core plugs, and multidimensional sandpacks) had a variety of applications, but their use for developing a reservoir-scale understanding of flow has lessened because they are more expensive and time consuming to develop, less flexible, and difficult to scale up to the reservoir scale. Such physical models are currently used in a narrow spectrum of specialized applications and often in conjunction with numerical simulation. However, physical flow models are undergoing a renaissance, helping to develop a better understanding of pore-scale flow, in the form of "flow chips," thanks to contemporary developments in miniaturization.

Computing and hardware architecture advancements are intimately intertwined with the developments in numerical reservoir simulation. In the early days of simulation, full-field stochastic modeling was unheard of, and engineers relied on deterministic sector and small-field models; in the past decade, full-field reservoir simulation has become almost a routine application. Large, complex fields are increasingly being modeled by coupling surface facilities (and their associated physics) with subsurface flow physics. Parallel processing, the racking up of layers and layers of central processing unit (CPU) chips, and the use of near-superlinear scalability have improved the modeling turnaround time. Cloud computing has further increased our capabilities by making affordable the use of a vast number of processors to simulation practitioners, on demand and from any location.

Numerical (field-scale) reservoir simulation and direct numerical pore-scale modeling share fundamental laws that govern the motion of multiphase, multicomponent fluids. These laws are based on the conservation of mass, momentum, and energy (Bird et al. 1960) expressed by the general Navier-Stokes equations that underpin computational fluid dynamics techniques (Versteeg and Malalasekera 1995) and a set of thermodynamics-based constitutive laws, such as the equations of state. A semi-empirical approach based on Darcy's law of viscous flow in porous media and its extension for multiphase flow is used in reservoir simulation, eliminating the need to solve the momentum balance equation (Collins 1961; Scheidegger 1974; Aziz and Settari 1979; Mattax and Dalton 1990; Ertekin et al. 2001). While this appears to be a simplification from a computational modeling perspective, significant complexity comes in through reservoir heterogeneities that influence key flow parameters, such as transmissibility, and the ensuing nonlinearity. In addition, fluid thermodynamics and uncertainties in other significant subsurface properties render reservoir flow simulators and their associated workflows highly complex. Instead of the lattice Boltzmann method and finite-volume techniques that are often used for the direct solution of fluid flows, finite-difference, finite-volume, and (to a lesser degree) variants of mixed finite-element techniques are commonly used in field-scale reservoir simulators.

In principle, one can compute the Navier-Stokes equations within the pore space at the microscale level to reveal some physical properties of the flow behavior at such a scale. In practice and for field-scale applications, however, it is not practical to simulate flow at the pore scale. Multiscale simulation technology has emerged over the past two decades, and in our opinion, its full

TAKEAWAYS

Since the first usable numerical reservoir simulators emerged in the early 1960s, continuous development has made them invaluable in managing hydrocarbon resources.

Numerical simulators have replaced electric analog models and have largely replaced scaled physical fluid-flow models.

Advances in distributed and parallel computing and hardware architecture developments have enabled routine use of full-field simulations.

Numerical reservoir simulators are based on the fundamental laws that govern the motion of multiphase, multicomponent fluids in combination with a multiphase extension of Darcy's law.

The incorporation of reservoir heterogeneity complexities and the ensuing nonlinearity, the intricacies of fluid thermodynamics, and the uncertainties of subsurface properties render reservoir simulators and their associated workflows highly complex.

Finite-difference, finite-volume, and (to a lesser-degree) variants of mixed finite-element techniques are commonly used in field-scale reservoir simulators.

Multiscale simulation technology (both at the physical- and algebraic-solution level) has emerged over the past two decades, and its full potential has not yet been reached.

potential has not yet been reached. In theory, the fundamental principle of multiscale simulation is to retain data at their pertinent spatial and temporal resolutions during the modeling and simulation.

Previous multiscale approaches, such as the dual-scale and hierarchical multilevel reservoir flow simulation models, spurred tremendous interest in exploiting interconnectivity between the temporal and spatial scales. Brandt (1977), Ramé and Killough (1992), Guérillot and Verdiere (1995), Guedes and Schiozer (1999), and Audigane and Blunt (2003) predominantly focused on aspects of upscaling to effective properties, most notably permeability, using volumetric and flow-based averages. Then, by imposing some boundary conditions on the subscale problem, one would be able to reconstruct solutions at the subscale level. Hou and Wu (1997), Jenny et al. (2003), and Aarnes et al. (2006) opened a new dimension in reservoir simulation in which upscaling to effective properties was not necessarily needed. The approach involved developing prolongation and restriction operators capable of encapsulating the physics of flow at the subscale level of interest. However, generalizability and process dependency remain challenges for upscaled models with multiphase effective properties.

TAKEAWAYS

Today's multiscale modeling approaches tackle crossing the chasm of scales and feature complicated physical problems.
It is likely multiscale technology will continue to develop and help fill in some of the gaps regarding multiscale disparities.

Cross-disciplinary (multiphysics) applications have gained traction in the past two decades, with the coupling of fluid flow and geomechanics. Recent advancements have made it possible to solve for the changes in mean stress, pressure, and saturations, both temporally and spatially.

Graphics processing unit (GPU) acceleration (Mukundakrishnan et al. 2015) combined with a new generation of solver preconditioning techniques, such as the algebraic multigrid family of preconditioners (Gries et al. 2014), deliver speedups to fine-scale models that are comparable to multiscale reservoir simulator formulations. The effectiveness of a given acceleration paradigm in a reservoir simulation model remains dependent on the heterogeneity of the partial differential equation coefficients, grid quality, and strength of the coupling between flow, transport, and the thermodynamic components of multiphase flow.

At first, these developments were geared toward enhancing computational efficiencies. Today's multiscale modeling approaches tackle crossing the chasm of scales and feature complicated physical problems, including compositional modeling (Hajibeygi and Tchelepi 2014), naturally fractured reservoirs (Ţene et al. 2016), establishing quantitative links between pore-scale and reservoir-scale physics (Mehmani and Tchelepi 2018; Alpak et al. 2018), and even big-data analytics and assimilation (de Moraes et al. 2020).

Cross-disciplinary (multiphysics) applications have also gained traction in the past two decades. Conventional reservoir simulators compute the pore-volume change through the rock compressibility concept, subject to the assumptions that in the reservoir (1) the total stress remains constant, (2) the loading condition is identical to the laboratory condition under which the rock compressibility was measured, and (3) local-bridging effects around a gridblock or a neighboring block can be assumed to be negligibly small (Chin et al. 2002). In addition, conventional reservoir simulators do not account for the interaction effects between the reservoir and its surrounding regions such as overburden, underburden, and sideburden. Reservoir properties (e.g., permeability) are typically assumed to be insensitive to the change of stress state in the rock compressibility approach. These assumptions, however, can restrict conventional reservoir simulators from performing realistic dynamic forecasts for reservoirs with complex geomechanical behaviors. With the integration of geomechanics, reservoir rock of complicated constitutive behavior can be rigorously simulated without geomechanical limitations and the coupled analysis can handle the effects of stress-sensitive properties and heterogeneity in the reservoir. The coupled analysis also considers the effects of surrounding regions/reservoir interaction and local bridging in the reservoir.

Explicit, iterative, and full coupling approaches have been proposed for the two-way coupled solution of flow and geomechanics equations (Minkoff et al. 2003; Dean et al. 2006; Prévost 2014). The advantages and disadvantages of coupling strategies have been established through comparative studies (Samier et al. 2006). Stability issues have been analyzed for alternative formulations (Kim et al. 2011). Poroelasto-plastic rock mechanics modeling techniques have been incorporated into coupled flow and geomechanics simulators (Alpak 2015). Field cases where coupled simulators led to an improved understanding of subsurface fluid and rock structure interactions have been reported (Coombe et al. 2001; Walters et al. 2002; Collins 2005; Tran et al. 2009).

Current Status

Hardware and accessibility have been the significant factors in the development of large-scale numerical models. At the core of reservoir simulation lies the numerical scheme that discretizes the continuous governing equations in space and time into a set of equations so that approximate numerical solutions can be obtained. Many of the advancements in today's reservoir simulation are mathematics-related (e.g., advanced discretization methods, adaptive and sophisticated gridding, linear and nonlinear solvers) or related to hardware and algorithmic in nature (e.g., parallel processing, CPU/GPU architectures, cloud computing), with some overlap between them.

TAKEAWAYS

The current reservoir simulation methods and technology are based on the developments in applied and computational mathematics and software engineering and hardware and are algorithmic in nature.

Geomechanics and fluid-flow simulation coupling is also central to optimizing unconventional developments, with the added complexity of hydraulic fracture propagation physics and the multicontinua (n-porosity/n-permeability) nature of the rock.

For the numerical simulation of unconventional resources, three different commercial approaches are available:

- Explicit modeling of the hydraulic fracturing process, upscaling, and the importing of the changes caused by the stimulation into the flow-based continuum model.
- The DFN concept and the adoption of a hybrid, finite-volume approach to account for fluid losses into the matrix.
- The standard finite-difference/finite-volume continuum-based approach with an added mean-stress equation.

Another niche multiphysics approach is the coupling of electromagnetics (Maxwell's equations) with reservoir fluid-flow equations.

Geomechanics and fluid-flow simulation coupling is central to optimizing unconventional developments, with the added complexity that hydraulic fracture propagation physics and the multicontinua (n-porosity/n-permeability) nature of the rock be included, leading to a truly multiscale multiphysics problem. Relative to conventional applications, hydraulic fracturing is a very fast process that requires significantly small timesteps to properly model the physics. It is also confined to a small volume around the wells, thus requiring significantly small gridblocks. In this scenario, the standard approach of coupling force (stress) and momentum (flow) solutions in a sequential manner results in significant material-balance violations.

A fully implicit approach where stress equations are added to the flow equations has overcome this bottleneck using certain simplifying assumptions (Dean and Schmidt 2009; Sherman et al. 2015; Settgast et al. 2017; Birkholzer et al. 2019; Rogers et al. 2020). Novel approaches are also being developed to simulate the propagation of fractures in a more computationally efficient manner that can be coupled with multiphase, multicomponent reservoir simulators (Wick et al. 2016). With these latest advancements, it is possible to solve for the changes in mean stress, pressure, and saturations, both temporally and spatially. In addition to the modeling of hydraulic fracturing processes, these advancements enable the calculation of the stress applied to fractures/rocks during the production process, improving the accuracy of pore-volume and permeability calculations.

For the numerical simulation of unconventional resources, three different commercial solutions are available. The first approach, which has been used in the industry for many decades, involves the explicit modeling of the hydraulic fracturing process, upscaling, and the importing of the changes caused by the stimulation into flow-based continuum models. The second commercially available approach centers on the discrete fracture network (DFN) concept. Because the DFN representation of the natural fractures and the weakness planes naturally lends itself to finite-element discretization, the industry has adopted a hybrid, finite-volume approach to account for the fluid losses into the matrix. The third commercially available approach uses the standard finite-difference/finite-volume continuum-based approach with an added mean-stress equation. In this approach, the volumetric density of the DFNs is represented as the Warren and Root dual-porosity matrix/fracture exchange (transmissibility) coefficient. Similar to hydraulic fracturing simulators, a “stress profile” criterion is used to initiate deformation for tensile fractures and other deformations associated with the overcoming of the cohesive, adhesive, and compressive strength of the rock fabric as a function of stress.

Another niche multiphysics approach is the coupling of electromagnetics (Maxwell’s equations) with reservoir fluid-flow equations. For example, formation Joule heating for heavy-oil applications requires the solution of low-frequency (direct-current limit) Maxwell’s equations in conjunction with thermal multiphase, multicomponent flow equations (Lashgari et al. 2016). The inversion of cross-well electromagnetic data for waterflood monitoring (Zhang and Hoteit 2019) and radio-frequency electromagnetic heating applications (Li et al. 2019) also require the coupling of reservoir simulation equations and Maxwell’s equations.

Evolving and Future Needs and Expectations

Despite the salient advancements in the field, we struggle to model several types of problems, including the behavior of unconventional reservoirs and their peculiar fluid storage and transport mechanisms, complex fault/fracture and facies systems, and other multiphysics reservoir modeling applications.

In unconventional reservoirs, the challenges fundamentally lie in our limited understanding of how nano-Darcy reservoirs behave at the macroscale level. Current studies on unconventionals are primarily focused on the microscale behavior of fluid flow and transport in porous media. The recent improvements and trends in the digital-rock-physics world and pore-scale modeling (e.g., molecular dynamics simulation, pore networks, and lattice Boltzmann), assisted by tremendous imaging capabilities, should not be confined to nanoscales. Unless currently lacking linkages to continuum-based finite-difference or finite-element simulations are established, the impact of pore-scale modeling will not last. The a priori assumption regarding the existence of the representative elemental volume may not be suitable in such reservoirs when the underpinning rule in reservoir simulation has always been a continuum assumption. It is imperative that we start looking at the physical problem with multiscale lenses.

Intrinsic to the success of simulation studies is reservoir characterization. The development of accurate reservoir characterization models that represent the detailed architecture of reservoirs and the spatial distribution of properties—most importantly those affecting the velocity fields—is of paramount importance. The characterization model must be complemented by accurate representations of the thermodynamic behaviors of hydrocarbon mixtures, from the reservoir to facilities and during the life of the field. It is also critically important to measure the constitutive relations that describe rock/fluid interactions and define their representations at all scales.

Field-scale numerical reservoir simulation is a multifaceted technology with a direct impact on effective decision making in the petroleum industry. However, there are challenges and opportunities awaiting the current technology. Moore’s law is exhibiting an increasingly flattening asymptote, and microchip manufacturing is approaching the physical miniaturization limit at the atom level. Much research is currently being devoted to quantum computing, and some of the early breakthroughs are quite promising. Code development could experience yet another paradigm shift in the very near future. An example is the penetration of GPU computing into the scientific computing community, and thus into reservoir simulator engines, over the past decade, compliments of the gaming industry.

TAKEAWAYS

New constitutive relations should be developed, and existing ones should be improved to describe the rock/fluid interactions at all scales to better represent flow phenomena in conventional, unconventional, and other emerging reservoir applications.
In unconventional reservoirs, the challenges fundamentally lie in the limited understanding of how nano-Darcy reservoirs behave at the macroscale level.

Cross-scale linkages are needed between pore-scale flow physics, digital-rock simulations, and Darcy-scale continuum field-scale simulations.

The development of accurate reservoir characterization models that represent the detailed reservoir architecture and the spatial distribution of properties—most importantly those affecting the velocity fields—is of paramount importance.

Although they will not solve all our challenges, deep learning, physics-based artificial-intelligence models, automation, cloud computing, the internet of things, and the digitalization of workflows are expected to play important roles in reservoir simulation workflows.

Current trends are also indicating that deep learning and its hybridization with physics-based models will play an even-more-significant role in the future of reservoir simulation workflows and at a lower level within solver machinery. Similarly, the development of quantum computing will have a significant impact on our algorithms. The fusion of artificial intelligence, automation, cloud computing, the internet of things, and the digitalization of workflows is rapidly affecting our industry. While many oil- and gas-industry standard operations and routine tasks naturally lend themselves to these technologies, these developments are not a magic wand to solve all our challenges.

> **TAKEAWAYS**
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> Publications from SPE and similar organizations will likely preserve the critical knowledge associated with the development of numerical simulation software.
>
> However, the experience gained through application cannot be as easily preserved or transferred, and for this, we will have to rely on the human-to-human transfer of experience.

Critical Knowledge and Experience To Be Preserved and Transferred

Publications from SPE and other organizations will likely ensure that the critical knowledge associated with the development of numerical simulation software will be preserved. History has shown that software providers may change but the technology is typically preserved and enhanced.

However, the experience gained through the application of these software packages cannot be as easily preserved or transferred. In the context of reservoir simulation, our obsession with automating software and displaying impressive user interfaces often overshadows a user’s ability to question the output and seek the most-relevant data. Until artificial-intelligence applications become truly intelligent, we will have to rely on the human-to-human transfer of experience for the appropriate application of these software packages. Existing publications and resources do not satisfactorily address the application-experience problem.

Enhanced Oil Recovery

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Introduction

Current primary depletion and waterflood or gasflood processes leave a significant fraction of oil in the reservoir. Enhanced oil recovery (EOR) processes can improve oil recovery through the injection of substances that are not native to the reservoir. These substances can include one or more of the following: steam, air, carbon dioxide (CO_2), enriched hydrocarbons, nitrogen (N_2), surfactants, alkali, polymers, microbial solutions, fresh water, and solutions incorporating nanoparticles; the injection could involve interwell flow or huff 'n' puff (HNP) processes. The potential worldwide recovery using EOR processes could be significantly greater than 1 trillion bbl if both conventional and unconventional reservoirs (URs) are included.

Despite more than 40 years of active use, EOR accounts for less than 10% of the oil produced daily. The factors that have resulted in slow adoption include

- That a limited number of processes might be applicable to any individual reservoir
- High operating costs for the injection fluids
- High capital costs for injectants and the facilities to mix or create those fluids or process their byproducts from production
- The significant expertise required to successfully run these facilities and manage reservoirs
- Long construction lead times and slow oil response times—cash-flow impact
- Slow uptake of cutting-edge technologies
- Competition with faster-responding projects for capital

TAKEAWAYS

EOR processes have been applied in various forms for more than 150 years in conventional reservoirs and most actively over the past 40 years.

The majority of EOR processes fall into the thermal, chemical, or solvent categories.

From the 1970s to the 2000s, steam injection was used most frequently and with the most success.

Interest in chemical EOR methods peaked in the 1980s, with alkaline-surfactant-polymer flooding now viewed as the most-promising chemical injection method.

Nitrogen and HC gas solvent injection were popular in the 1950–1970's. Today, HC gas solvent floods are found in areas where the gas has little value except as an injectant, i.e., North Slope and unconventional EOR pilots.

History, Background, and Original Concepts

EOR processes have been applied in various forms for more than 150 years in conventional reservoirs and most actively over the past 40 years. EOR processes improve oil recovery through a focus on one or more recovery mechanism efficiencies. Microscopic displacement efficiency can be enhanced through the reduction of interfacial tension (IFT), improved miscibility, oil swelling, and oil viscosity reduction. Improvements in the volumetric sweep efficiency are primarily driven by a reduced mobility ratio, but fluid densities can be used to enhance volumetric sweep in some reservoirs.

The majority of EOR processes fall into the thermal, chemical, or solvent categories. Thermal methods have been around since 1865, with the underlying goal to reduce the oil viscosity and allow the oil to flow more easily to the producing wellbore (Perry and Warner 1865). Since then, various approaches—including the injection of air and steam—have been tried, with steam injection used in the most EOR projects around the world from the 1970s to the 2000s and producing the greatest EOR benefits.

Chemical EOR trials and interest in chemical methods peaked in the 1980s, with polymer flooding being the most-popular technique. Since 1990, few new projects have been implemented, except in China. Polymer flooding is now considered a mature technology, and research efforts continue to investigate efficiency gains from polymer flooding. Alkaline-surfactant-polymer flooding is now viewed as the most-promising chemical injection method, and a pilot injection was started in China in 1994 (Alvarado and Manrique 2010).

Solvent EOR has been applied, with N_2 and hydrocarbon-gas projects favored between the 1950s and 1970s, primarily as pressure maintenance projects. Since then, these projects have declined in popularity, except for miscible hydrocarbon injection projects on the North Slope in Alaska. CO_2 was successfully applied in the US in carbonate reservoirs in the Permian Basin starting in 1972 and in sandstone formations in Mississippi and Wyoming in the 1980s. Only a handful of CO_2 injection projects have been attempted outside the US, primarily because of a lack of economical sources of CO_2. On the other hand, interest has recently grown regarding the use of CO_2 and hydrocarbon gas or enriched gas for HNP EOR in North American unconventional reservoirs (Hoffman and Evans 2016; Alfarge et al. 2017; Sahni and Liu 2018; Nagarajan et al. 2020).

Current Status

Most EOR activity has occurred over the past 40 years or more using thermal, solvent, chemical, or other EOR processes, or a combination thereof.

Thermal processes, which are the most mature and well-understood of the EOR processes, include cyclic steam, steamflood, steam-assisted gravity drainage (SAGD), and high-pressure air injection (also called in-situ combustion). Because thermal processes generally target higher-viscosity oils, the mobility benefit of a viscosity reduction greatly improves the recovery efficiency. Steam-based processes raise the temperature of the oil and reduce oil viscosity, which increase oil recovery. To be efficient, these processes require lower pressures, which is why they are mostly applied in reservoirs at shallower depths.

Steamflood has been used in cyclic-steam injection to develop a swept area around wells (Burns 1969), which can be converted to a flood after sufficient injectivity has been established or the steam/oil ratio has declined. In SAGD, a horizontal injector is drilled above a horizontal producer, and the heat from injected steam is used to reduce viscosity and the density difference to enhance oil drainage in and near the steam chest. There is also toe-to-heel air injection, with and without the catalytic conversion of heavy oils to lighter oils. High-pressure air injection thermally oxidizes a portion of the heavier hydrocarbons to create heat and generate CO_2 and steam, thereby significantly reducing the oil viscosity, swelling the oil, and pushing the oil toward producing wells.

Thermal processes were the primary EOR method for many years [peaking at 500 million BOPD in 1985 and declining to approximately 300 million BOPD in 2014 (Koottungal 2014)], but their use is in decline because of a lack of high-viscosity shallow reservoirs that have not already been flooded and the comparably high cost of steam.

Solvent processes have eclipsed thermal processes both in terms of EOR production and their frequency of use in projects, primarily driven by miscible CO_2 injection. Other solvent processes include the injection of enriched hydrocarbon gas, flue gas, and N_2. These processes are most effective where reservoir pressure is above the minimum miscibility pressure (MMP), and they tend to exchange mobility control for a substantially improved microscopic displacement efficiency because of oil swelling, an oil viscosity reduction, and an IFT reduction. Water-alternating-gas (WAG) injection and foam injection improve mobility control through relative permeability effects to block zones that are more permeable and homogenize the sweep front, reducing fingering and injectant channeling. More recently, laboratory studies and field trials in unconventional reservoirs have used gas-injection HNP methods, where the key mechanisms are primarily oil swelling, viscosity reduction, and IFT reduction (Hoffman and Evans 2016).

TAKEAWAYS

Although the thermal processes are the most-mature EOR technologies, their use has been in decline because of a lack of high-viscosity, unflooded, shallow reservoirs and the high cost of steam.

Solvent processes have surpassed thermal processes in both production and frequency of use.

Recent laboratory studies and field trials have indicated the EOR potential of gas-injection HNP in unconventional reservoirs.

CO_2 is the dominant solvent for EOR, but it has limited natural availability in most areas. The economics of the use of anthropogenic CO_2 for EOR is currently not established.

Foam flooding for improved mobility control has been tested but is not used routinely.

The chemical EOR process is quite flexible and can be applied in any geographic location, but the surfactant/polymer process must be designed for specific reservoirs.

Other processes—including the use of microbes, nanoparticles, low salinity, polymers with low salinity, and ionic liquids—have shown promise but tend to be much less well-understood.

Combination processes can improve recovery over that of each individual process but add expense and complexity.

Hydrocarbon gas or natural gas liquids are rarely used in solvent processes because of their economic value relative to their value as injectants, so they are typically considered for solvent injection only where they have no market or little value (e.g., in the North Slope of Alaska). Other gases have been used, but the dominant solvent is CO_2, which has a limited natural availability in most areas. Exceptions are the Permian Basin, the southeastern US, and, to a lesser extent, the Rocky Mountains, which have natural, albeit declining, CO_2 sources nearby. A lack of large-volume CO_2 sources near fields has limited CO_2 flooding in other parts of the world. Recently, the industry has begun to explore anthropogenic sources, which could result in a broader availability of CO_2, but the technical and economic viability of using anthropogenic CO_2 for EOR is currently not established. While other gases (such as methane-rich natural gas, N_2, and flue gas) have been used in EOR floods, their MMP is substantially higher than that of hydrocarbon gas or CO_2, making miscibility in the reservoir difficult to achieve without exceeding the fracture pressure of the reservoir. Foam flooding for improved mobility control has been tested but is not used routinely.

Chemical processes include the injection of polymers only or combinations of surfactants and polymers. Surfactants reduce IFT to mobilize trapped oil and improve displacement efficiency. Polymers increase viscosity and improve the sweep efficiency. Alkalis are often added to reduce surfactant adsorption, and cosolvents are added to improve phase behavior.

The chemical EOR process is quite flexible and can be applied in any geographic location, but the surfactant/polymer process must be designed for specific reservoirs. Although polymer flooding has been and is being applied in many reservoirs around the world, surfactant flooding has been piloted for many reservoirs but has seen limited fieldwide application because of long response times and the high level of expertise required.

Other processes include the use of microbes, nanoparticles, low salinity, polymers with low salinity, and ionic liquids. These processes tend to be immature and much less well-understood, but they have shown interesting results in the laboratory. These studies have shown that ions and nanoparticles can reduce IFT and the contact angle, helping to make solid surfaces more water-wet and blocking pore throats to divert injection to other pores that have not been swept (Kazemzadeh et al. 2019). With microbial EOR, microbes are introduced to partially digest long hydrocarbon molecules (reduced viscosity), to generate biosurfactants (chemical EOR), or to emit CO_2 (solvent EOR) (Tullo 2009). In laboratory experiments, low-salinity waterfloods appear to modify the wettability of the rock so that it is more water-wet (Shi et al. 2021), and polymer treatments with changes in salinity have been shown to increase recovery (Sotomayor et al. 2021).

In addition, using a combination of processes (such as foam gas/surfactant with a WAG process) can improve recovery over that of any individual process but comes at an additional expense and adds complexity to the operation. These processes are in the early stages, with no true experts in the industry because there have been few pilots, and even fewer successful pilots. Other combination processes, which focus on improved mobility control for otherwise well-known processes, include steam/foam, steam/solvent, steam and gas push, CO_2 + solvent gas vapor extraction, and nanoparticles in foam.

Evolving and Future Needs and Expectations

The average primary recovery factor for URs is typically less than 10% (Sheng 2017), indicating enormous potential for EOR processes in these resources, but because of extensive induced fracturing between wells and very low matrix permeabilities, the process has been changed from a flood to an HNP process. Laboratory and numerical modeling studies conducted for cyclic-gas injection in URs show that optimizing the process variables (cycle number, soak/injection/production times) can result in a substantial increase in oil recovery at acceptable utilization ratios (Gamadi et al. 2014). In addition, recent field trial results have shown that natural-gas injection could help recover 30 to 70% more oil (over primary depletion) from Eagle Ford Shale wells (Sheng 2017). Hence, based on these early encouraging results, there has been an exponential increase in research joint industry projects and field trials for gas EOR in unconventional plays across North America (Rassenfoss 2017).

The application of chemicals, such as surfactants, in URs, both as completion additives and cyclic EOR injectants, has also recently gained research attention. The key mechanisms for surfactant EOR in unconventional plays include wettability alteration, IFT reduction, fracture damage removal, and near-wellbore repressurization (Zhang et al. 2019). However, unlike gas EOR, field trial success for chemical EOR injectants in URs has yet to be reported (Rassenfoss 2017). The very low recovery factors in these reservoirs and the large volume of potential target hydrocarbon pore volumes (HCPVs) present a valuable opportunity for the use of EOR in shales.

> **TAKEAWAYS**
>
> The basic EOR concepts must be preserved.
>
> Future practitioners should understand the relationship between the recovery factor, displacement efficiency, and volumetric sweep efficiency and how these factors are affected by fluid and reservoir rock properties.
>
> Phase behavior and rock/fluid interactions during EOR should be understood.
>
> Geology is the most important factor determining the success of an EOR project.
>
> Knowledge of formation damage during EOR is also important.

In offshore reservoirs, the implementation of these processes can be technically and economically challenging because of the low number of wells, relative inaccessibility of the wells, and limited platform capacity. Chemical EOR might be the easiest to implement because it would only require an addition to the already-existing waterflood equipment, and pattern arrangements are already in place. Gas injection could be a possibility, but the space required—for the process equipment to prepare the injectant or manage the additional fluids produced and the compressors to inject large volumes of gas—is a considerable limitation. Some facilities could be located onshore if they are near enough, with pipeline(s) and other equipment to transfer the fluids. As with the North Slope, there could be other drivers that enhance the economics and encourage implementation of EOR processes. Five different EOR processes (hydrocarbon miscible gas injection, WAG, simultaneous WAG, foam-assisted WAG, and microbial EOR) have been tested in the North Sea since 1975 (Teigland and Kleppe 2006). WAG flooding appears to be the most commonly accepted EOR practice in the North

Sea, with 63% of the EOR projects located on the Norwegian continental shelf and another 32% located on the UK continental shelf.

Recently, novel surfactants that can be applied in high-temperature and moderately high-salinity (equivalent to seawater) reservoirs have been developed. Because common polymers are not stable in such conditions, new polymers (synthetic and plant-based) are also being developed. These new biopolymers could offer environmentally friendly approaches that might be lacking in today's suite of chemicals.

A drawback of EOR processes is the slow oil response time. Tight reservoirs only exacerbate this problem; with low throughput (%HCPV injected/yr), the injection front progresses slowly, delaying the onset of oil production from the process. In many cases, more than 20% HCPV must be injected before the fastest-zone oil response appears at the production well. If the throughput is 2% or less, it can take more than 10 years for oil response, which is disruptive to the economics of any project, and other approaches might need to be considered. Hydraulic fracturing could be an option to increase throughput, but it reduces sweep efficiency.

In high-pressure air injection, the combustion-front velocity must be maintained within the appropriate narrow range unless the formation temperature is sufficiently high to auto reignite the combustion front with continued air injection. If this risk can be alleviated, high-pressure air injection could be more broadly used in many mature oil fields across the world because air is readily available in all locations.

The key challenges for surfactant flooding are surfactant retention and finding ultralow IFT formulations for harsh-condition reservoirs. For polymer flooding, the challenges are maintaining polymer stability at high temperatures and high salinities and transporting polymers in low-permeability rocks.

TAKEAWAYS

Based on early encouraging results, there has been an exponential increase in research joint industry projects and field trials for gas EOR in unconventional plays across North America.

The application of surfactants in URs has also recently gained research attention, but field trial success for chemical EOR injectants in URs has yet to be reported.

Implementing EOR processes can be technically and economically challenging offshore; chemical EOR may be the easiest to use, while gas injection could be a possibility.

Novel surfactants that can be applied in high-temperature and moderately high-salinity reservoirs have been recently developed.

A drawback of EOR processes is the slow oil response time; hydraulic fracturing could be considered to increase throughput, but it reduces sweep efficiency.

If the combustion-front velocity risk can be alleviated, high-pressure air injection potentially offers a broader application in many mature oil fields because air is readily available.

Surfactant retention and finding ultralow IFT formulations for harsh-condition reservoirs are the key challenges for surfactant flooding. For polymer flooding, polymer stability in high-temperature and high-salinity reservoirs and the transport of polymers in low-permeability rocks are the primary challenges.

Critical Knowledge and Experience To Be Preserved and Transferred

It is essential that knowledge of the basic EOR concepts and state-of-the-art EOR methods be preserved (Lake et al. 2014; Kamal et al. 2017; Agi et al. 2018; Green and Willhite 2018; Gbadamosi et al. 2019). The basic concepts include an understanding of the forces that help or hinder recovery, such as viscous forces, capillary forces, applied pressure forces, and gravity.

The recovery factor is determined by the microscopic displacement efficiency and the volumetric sweep efficiency. It is important that future practitioners understand both the relationship between these essential factors and how they are affected by fluid (both in situ and injected) and reservoir rock properties. Recognizing reservoir geology as a key for success of an EOR project is also essential.

Other important concepts that must be understood include phase behavior and rock/fluid interactions during EOR. Practitioners should also be aware of how formation damage occurs during EOR processes and what can be done to mitigate it.

Well Performance

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Introduction
Well performance analysis generally refers to the analysis and interpretation of production rates and pressures from producing wells to estimate ultimate recovery and evaluate dynamic reservoir properties (permeability and other reservoir properties, depending on the geological model) and completion parameters (such as the skin factor, fracture half-length). More broadly, results from well performance analyses provide insights into and facilitate reservoir characterization, field development planning, and completion optimization.

Well performance analyses (i.e., analyses of production and pressure data) can be categorized as follows:
- Time/rate analysis, or decline curve analysis (DCA)
- Time/pressure data analysis, or pressure transient analysis (PTA)
- Time/rate/pressure data analysis, or rate transient analysis (RTA)

However, well performance analysis should not be solely limited to production rate and pressure data measurements and analyses. Instead, using these methods in conjunction with key subsurface data and completion diagnostics provides a better understanding of a system and leads to better decisions.

History, Background, and Original Concepts
Methods for DCA are generally data driven and tend to rely on empirical equations and/or relations derived from analytical expressions using idealized conditions or assumptions (e.g., the constant wellbore pressure case). Arps' exponential and hyperbolic decline relations [presented by Arps (1945) but first published by Johnson and Bollens (1927)] are still widely used in the industry to estimate ultimate recovery and book reserves and resources.

The DCA literature has greatly expanded over the past 10 years, coincident with the exploitation of low-/ultralow-permeability (unconventional) reservoirs. Today, many decline curve relations are available in the literature that are based on a certain characteristic behavior and/or related to a specific flow regime. While some of these "transient" solutions are based on theoretical considerations, the assumptions and applications are often empirically derived. Many of these relations have similar characteristics, and thus far, none are fully rigorous; all proposed relations have some limiting condition(s) and/or assumption(s). As one would expect, the absence of relatively long-term production data (> 10–15 years) from unconventional reservoirs presents significant challenges for empirical methods. Many models can match the historical production, but there is limited data-based support for extrapolation to 30 years and beyond. Additionally, decline-analysis-based methodologies are not capable of addressing changes in well production because of factors such as artificial lift, changes in choke size, the impact of offset-well production, and fracture hits.

In contrast, analysis methods based on time/rate/pressure data are derived from the solution of the diffusivity equation. Despite the mathematical rigor of the solution process, the diffusivity equation involves the Darcy-flow assumption and approximate representations of well and reservoir geometry, boundary conditions, and heterogeneities. In this context, conventional analyses of well performance using time/rate/pressure data are tied to traditional concepts such as permeability, porosity, fracture surface area, and standard reservoir boundaries (circular, rectangular), which are imposed by the mathematical model used in the analysis and its solution conditions. Well/reservoir models include representations of various well types, such as wells in homogeneous reservoirs, horizontal wells, fractured vertical wells, and horizontal wells with multiple fractures. Currently, software packages for well performance analysis include a large inventory of models—all based on Darcy's law, as well as on traditional fluid thermodynamics and reservoir model constructs—with which to analyze, interpret, and forecast production data.

As a result, the application of traditional RTA/PTA/DCA concepts in unconventional reservoirs could be problematic because of the unique nature of these systems [i.e., very low permeability, self-sourced production, organic porosity, complex fracture geometry(s)]. At present, there are no new methodologies specific to nanoscale storage and transport (i.e., molecular-level storage and Knudsen-type flow behavior), although there are new means of modeling such behavior (e.g., anomalous diffusion, "fractal" models that act as proxies). This leaves us with empirical decline curve models and traditional Darcy-flow-type models, in addition to conventional porosity and permeability concepts. Complex fracture geometries could be addressed by increasing the capabilities of reservoir modeling software packages. However, it should be emphasized that even complex models retain some connection to traditional permeability and porosity concepts. (Although the flow geometry might be quite complex, the "bulk" behavior appears to be represented by "normal" permeability and porosity concepts.)

TAKEAWAYS

DCA methods are generally data driven and tend to rely on empirical equations and/or relations derived from analytical expressions using idealized conditions or assumptions.

The absence of relatively long-term production data from unconventional reservoirs presents significant challenges for empirical methods, with limited support for extrapolation to 30 years and beyond.

Conventional analyses of well performance using time/rate/pressure data are tied to traditional concepts such as Darcy flow, permeability, porosity, fracture surface area, and standard reservoir boundaries, which are imposed by the mathematical model used in the analysis and its solution conditions.

Because of the unique nature of unconventional systems, using traditional RTA/PTA/DCA concepts in these reservoirs could be problematic.

Reservoir simulation provides a more-complete view and better understanding of a system, and reservoir simulation models could be adapted to include nearly any or all aspects of production mechanisms.

Well performance analysis studies conducted using reservoir simulation provide a more-complete view of the well and reservoir as a system, which in turn leads to a better understanding of the system and the key production mechanisms (and, in particular, an ability to establish the effects of infill wells and different production schemes). Reservoir simulation studies require the availability and integration of data from all disciplines—geology/geophysics, petrophysics, geomechanics, reservoir engineering, production, and completions—although such integration might not be possible in all cases and is often cost prohibitive in terms of time and resources. Many operators are also leaning toward integrating data-driven methodologies into numerical simulation to allow for comprehensive decision making, especially in fast-paced unconventional reservoir development.

Last, because reservoir simulation models are much more complex than RTA/PTA/DCA techniques based on single-well models, reservoir simulation models could be adapted to include nearly any or all aspects of production mechanisms [i.e., geomodel(s), phase-behavior characterization, complex flow geometries (e.g., discrete fracture networks), multiwell production, staged/developed (e.g., parent/child well cases)].

Current Status

Well performance analysis based on PTA/RTA techniques is becoming more popular and has benefitted from increased computational power and data acquisition. The primary limitation of these techniques is associated with a lack of supplementary data, which would be used to constrain analyses and reduce uncertainty. The quality of time/rate/pressure data is extremely important; currently, production data can be rendered hourly (or less), and the continuous measurement of bottomhole pressures (and temperatures) is being more frequent used. These data provide significantly better resolution of production and pressure trends, particularly for analysis and forecasting.

TAKEAWAYS

Well performance analysis using PTA/RTA techniques has gained in popularity and benefitted from increased computational power and data acquisition, but the primary limitation is associated with a lack of supplementary data to constrain analysis.

The quality of time/rate/pressure data is very important.

With the advent of large-scale unconventional reservoir development, production diagnostic techniques have become critical tools for performance assessment.

The deliverables from well performance analyses provide for the optimization of well performance, establishment of factors that control production and reserves, and benchmarking of productivity across an area of interest.

Performance-based workflows could be used to develop "recipes" for field developments that would be tied to well spacing, targets, completion size and stages, flowback strategy, choke management, and artificial lift.

With the advent of large-scale unconventional reservoir development, diagnostic techniques have become critical tools for performance assessment before the analysis/forecasting model is constructed. More specifically, production diagnostic techniques are essential for understanding flow regimes, establishing characteristic flow behavior that can be translated to decline curve parameters, and establishing productivity metrics. These metrics can include volume-based metrics [e.g., cumulative oil/gas/water production at 1/3/6/9/12 months, pressures (average flowing pressure over 1 month, pressure gradient, initial pressure)] and productivity indices (e.g., establishing linear flow behavior from specialized plots).

Production diagnostic techniques also allow for the performance of multiple wells to be compared and specifically provide the ability to contrast differences resulting from aspects such as well completions, reservoir target intervals, and lateral well spacing. Completion metrics (i.e., well completion and well stimulation parameters) can be easily integrated into models for the analysis of well performance, as well as to create correlations with well performance metrics.

As a practice, the use of well performance analysis methods is crucial for workflows encompassing well completion design, reservoir characterization, and field development. Perhaps more importantly, the deliverables from well performance analyses provide for the optimization of well performance, establishment of factors that control production and reserves, and benchmarking of productivity across an area of interest. Performance-based workflows could be used to develop "recipes" for field developments that would be tied to well spacing, targets, completion size and stages, flowback strategy, choke management, and artificial lift.

Evolving and Future Needs and Expectations

At present, the industry's priority area of interest is optimizing horizontal-well spacing in unconventional reservoirs. Many operators in North America have suffered from potential "overdrilling" and the overestimation of future production (Olson 2019). Without clear learnings and guidance, other emerging plays could suffer the same fates.

In addition, the effects of depletion on new wells caused by existing producing wells, and vice versa (the so-called parent/child effects), have yet to be properly quantified or understood. One of the primary goals of reservoir engineering is to determine the minimum number of wells that it would take to maximize recovery from a given field or play, a task that is particularly difficult for unconventional plays. Attempts to provide "cube" or "tank" developments [i.e., where well patterns are prescribed and drilling/completion/stimulation/flowback are performed simultaneously (or nearly so)] have delivered mixed results. [Most recent reports have been negative (Jacobs 2019).]

These circumstances take us back to "fit-for-purpose" designs based on geology and well development strategies (i.e., tailored completions and stimulations). Such fit-for-purpose

TAKEAWAYS

Practical and more-accurate methods are needed to optimize horizontal-well spacing on the basis of well performance data.

The quantification of the parent/child effect in workflows is needed.

Using fit-for-purpose designs based on geology and well development strategies will require more design considerations and more diagnostic/analysis/modeling efforts for the corresponding well performance data.

Future efforts in unconventional reservoirs will primarily focus on understanding the fundamental behavior of these systems and incorporate that understanding into physical models that can be used to analyze, interpret, and forecast production data.

Improvements in production surveillance and diagnostic interpretation techniques will add significantly to the value obtained from performance-based reservoir characterization/development workflows.

methods will require more design considerations and more diagnostic/analysis/modeling efforts for the corresponding well performance data. DCA is not designed for analysis during transient behavior, and RTA/PTA interpretations are dependent on the availability and quality of data for analysis. Multidisciplinary data are also needed in these cases for the cross-validation of outputs and to reduce the inherent uncertainty driven by base assumptions underlying such analyses in unconventional reservoirs. As such, future efforts in well performance analysis in unconventional reservoirs will primarily focus on understanding the fundamental behavior of these systems and incorporate that understanding into physical models that can be used to analyze, interpret, and forecast production data from these reservoirs.

In addition, improvements in production surveillance and diagnostic interpretation techniques would add significantly to the value obtained from performance-based reservoir characterization/development workflows. A considerable number of operators often ignore or pay little attention to the collection of these types of data, not realizing the value of such information, which could potentially lead to improved well completions, targeting, and well spacing.

Critical Knowledge and Experience To Be Preserved and Transferred

The analysis of well performance requires not only high-quality data but also a good understanding of reservoir flow dynamics and the effects of physical reservoir properties, well architecture, and the production history on well responses. As for the high-quality data, data acquisition and production surveillance techniques, tools, and protocols should be well-documented, updated, and transferred to future generations. It is equally important to document the state-of-the-art methods used in cross-validation and constraining analysis techniques and best practices.

Regarding the interpretation of well performance, the diagnostic meaning of data should take precedence over statistical properties or mathematical aspects. The automated analysis of data—by means of software or using simple regression or artificial intelligence and machine-learning techniques—should not be allowed to supersede human interpretation. Analysts should be well-trained to avoid overconfidence or blind trust in the tools and procedures available to them or commonly used by others. The theoretical bases and limitations of the legacy well performance analysis tools should be understood, and analysts must be required to have the relevant theoretical background for the tools they use.

TAKEAWAYS

Well performance analysts should be well-versed in reservoir flow dynamics and the effects of physical reservoir properties, well architecture, and the production history on well responses.

Data acquisition and production surveillance techniques, tools, and protocols should be documented, regularly updated, and transferred to future generations.

State-of-the-art methods in cross-validation and constraining analysis techniques and best practices must be documented.

The diagnostic meaning of data should take precedence over statistical properties or mathematical aspects.

Human interpretation should supersede automated well performance analyses.

Analysts must be educated and trained on the theoretical bases and limitations of the legacy well performance analysis tools.

Reservoir Management

Introduction

The objective of reservoir management is to optimize hydrocarbon recovery from a reservoir with respect to capital investments and operating expenses (Thakur 1996; Fanchi 2002). That is, reservoir management is the process of considering tradeoffs between the benefits, costs, and risks of different uses of technical, financial, and human resources on the basis of data, knowledge, and experience to achieve optimal recovery. In a broader sense, management is not a science, nor is it an art; it is a "practice" (Peter F Drucker on Management 1997). In general, management is a dynamic practice because it has to keep up with the continuously changing nature of business needs and processes, financial and socioeconomic conditions, and human behavior, in addition to the complex interactions of its constituents. Arguably, reservoir management is even more dynamic because it starts when there is no or very little information about the subject reservoir and evolves with the field development as more knowledge and better characterization of the reservoir become available. In addition to the risks considered in a standard management practice, reservoir management has to account for the risks that result from geological uncertainties and the inherent limits of our ability to fully characterize reservoirs and flow processes. In reservoir management, these flaws are mitigated by the systematic application of integrated, multidisciplinary technologies (Fanchi 2002). Most of the tools used in reservoir management have been discussed in previous sections of this document. The Reservoir Management section discusses those that remain, namely data analytics, artificial intelligence, and machine learning; field-scale projects; reserves; and project economics. Leadership is not discussed because management is not leadership. "Management is doing things right; leadership is doing the right things" (Drucker 2001).

Data Analytics, Artificial Intelligence, and Machine Learning

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Introduction

Aided by technological developments, recent years have witnessed a rapid increase in the volume of data collected in oilfield operations (Sankaran et al. 2020). Challenges—especially in the description of the static and dynamic characteristics of unconventional resources and the downturn of the oil industry—have solidified the necessity of using collected data more effectively for better modeling, analysis, uncertainty quantification, and decision making in reservoir engineering applications. The proper management and useful analysis of collected data to understand reservoir characteristics and behavior for both diagnostic and performance-forecasting purposes have become critical components of modern reservoir engineering practice.

History, Background, and Original Concepts

The original concepts in data analytics, artificial intelligence (AI), and machine learning (ML) can be grouped into the following categories: data organization, visualization, ML for classification, ML for prediction, modeling strategies, uncertainty and risk, and decision making.

Data organization refers to how data sets are classified and organized to be more useful. Digital oilfield technologies enable the collection of greater volumes of data in shorter time periods. It is critical to properly use cloud technologies and database applications to organize data sets for effective analysis, analytics, and modeling.

Business intelligence tools are used to better visualize and analyze data. Interactive map-based dashboards make analysis easier by incorporating engineering and geological knowledge and regional expertise. These efforts have been supported by digital oilfield initiatives.

Classification is the problem of predicting a categorical output (e.g., high/low). Typical classification problems in reservoir engineering include the classification of rock facies (lithofacies, petrofacies, seismic), fluid types, production anomalies, flow regimes, drive mechanisms, and well/reservoir quality. When the classes are known and can be explicitly defined, supervised learning allows patterns to be found that link the input variables to these defined classes. Neural networks, support vector machines, random forests, fuzzy logic, and rule-based systems are used for supervised learning. For example, when a series of well logs is mapped onto lithological descriptions in a given reservoir using subject-matter expertise, the data set can be used for classification-based training using a supervised learning algorithm. Such a model can later be used for the automatic classification of well-log intervals to identify the lithology in new wells. When the classes are not explicitly known, unsupervised learning methods identify certain clusters from the patterns in the data by quantifying the similarity between individual data points. This allows cases with similar characteristics in the data set to be separated into groups. Clustering algorithms as well as some types of neural networks, such as self-organizing maps, are considered to be unsupervised learning algorithms. For example, on the basis of reservoir and performance characteristics, groups of wells with similar characteristics can be created. Additional analysis can be performed to understand the distinct features of the well groups.

In predictive modeling, a mapping function is learned from the inputs to the outputs (i.e., function approximation). Typical problems in reservoir engineering include the estimation of rock properties (porosity, permeability, saturation) and fluid properties (API gravity, gas gravity, solution gas/oil ratio, saturation pressure) and the prediction of reservoir recovery and production rate profiles. For example, historical performance (e.g., the oil rate), reservoir characteristics, and historical operational conditions can be used to build an integrated data set. A model can be trained that uses reservoir and operational parameters as inputs and oil recovery as an output. Similar to a numerical reservoir model, the trained (history-matched) model can be used to forecast recovery under different conditions. Other types of predictive models include various empirical correlations that have been used for estimating rock and fluid properties using laboratory samples from various reservoirs. Reservoir analogs and physical equations have also been used for predicting reservoir recovery and associated production rate profiles.

Predictive and classifier models are developed by following a systematic workflow that includes designing the parametric representation of the problem, choosing the ML algorithm, and training, evaluating, selecting, and validating the model. Some types of ML algorithms help in gaining insights regarding the importance of different variables in the model, which creates room for diagnostic analytics.

In terms of modeling strategies, historically, reservoir modeling methods evolved to describe the physics of fluid flow through porous media for pressure transient analysis and numerical simulation. Notably, complexities arise because of complex reservoir geometry (faulted and fractured reservoirs), hydrocarbon phase behavior, rock/fluid interfaces, and other nonlinearities. With the advent of high-performance computing, numerical simulation has become well-

TAKEAWAYS

It is critical to properly use cloud technologies and database applications to organize data sets for effective analysis, analytics, and modeling.

Business intelligence/analytics tools are used to achieve better visualization.

ML applications can be used for classification and prediction problems.

With the advent of high-performance computing, numerical simulation has become well-accepted as a viable modeling method for significant capital decisions.

Risk and uncertainty in modeling are managed through integrated representations of uncertainty sources and formalisms for handling and modeling uncertainty.

All models designed for classification and prediction purposes can be used for decision making.

accepted as a viable modeling method in the industry for significant capital decisions. However, three key challenges must be addressed when using numerical simulation: (1) The underlying physics governing fluid flow must be adequately captured and fit-for-purpose, (2) the reservoir characterization must be adequate for forward modeling methods, and (3) the time scale needed for computing efforts must be sufficient for decision-making purposes for optimization under uncertainty.

On the topic of uncertainty and risk, decision analysis in field development is strongly related to risk because of the uncertainties in the data and modeling methods. Current approaches to deal with uncertainty focus on integrated representations of uncertainty sources and formalisms for handling and modeling uncertainty.

Finally, all models designed for classification and prediction purposes can be used for decision making. For example, a reservoir characterization model can be used to identify sweet spots and infill-well locations. Sometimes, subject-matter expertise and physics can be incorporated into these models to enhance their classification and prediction capabilities.

Current Status

The data management strategies of most oil and gas companies with respect to their core applications have not yet been designed to handle big data or support analytics on a large scale. While database technologies have significantly improved, the systems that are being used are often decades old and were not built for rapid input/output operations or unstructured data management.

In terms of visualization, business intelligence tools are primarily being used to understand reservoir and well performance using real field data and to identify underperforming producers and injectors so timely action can be taken (Popa and Cassidy 2012). Analyzing the quality of history matching in reservoir simulation is another common use.

AI/ML methods are ideally suited for petrophysics and reservoir characterization applications that include multiple scales and types of data (from seismic to cores, logs). Since the earliest use of AI/ML methods in the petroleum industry, reservoir characterization has been a primary application area because of its inverse and data-driven nature. Lithology/ flow-unit identification and sweet-spot identification have been among the successful classification-type applications (Bestagini et al. 2017). These applications are currently being expanded to unconventional reservoirs, where they have more value (Hoeink and Zambrano 2017).

In terms of prediction, AI/ML was first applied to reservoir rock and fluid property estimations from experimental data (e.g., logs, cores) to develop correlations (McCain et al. 1998; El-Sebakhy et al. 2007). AI/ML was then used with synthetic log generation, seismic inversion (Artun and Mohaghegh 2011), and the integration of multiple sets of data for sweet-spot identification (Ertekin 2021). Data-driven models have also been used successfully in the performance forecasting of unconventional reservoirs (Esmaili and Mohaghegh 2016; Al-Alwani et al. 2019) in cases where decline curves have failed or forecasting is difficult because of heterogeneities.

In terms of modeling strategies, ML techniques have been used successfully to create surrogates for reservoir simulation models (Amini and Mohaghegh 2019). This allows for complex reservoir studies that require many reservoir simulation runs to be accelerated. Other reduced-physics and reduced-complexity modeling strategies—such as streamlines, capacitance-resistance models, diffusive time of flight, model order reduction—have been applied to speed up reservoir performance predictions.

On the topic of uncertainty and risk, the combination of many uncertainty variables and complex models that require long simulation runs requires the consideration of other factors, such as the selection of critical variables through sensitivity analysis, proxies of objective functions, and the aggregation of variables. In practice, with high-fidelity (physics-based simulation) models, optimization is seldom considered because of the great computational effort required and lack of feasibility. The computational speed of data-driven models makes the quantification and analysis of uncertainty very practical when compared to high-fidelity models.

ML-based models have been successfully used for both classification and prediction purposes to make development decisions related to unconventional and mature conventional fields regarding the optimization of well count, location, trajectory, and completions; enhanced oil recovery; waterflooding; and the selection of candidate wells for restimulation (Kaushik et al. 2017; Burton et al. 2019; Zhou and Lascaud 2019).

One of the primary shortcomings of data-driven models is that the inner workings of these models

TAKEAWAYS

The data management strategies of most oil and gas companies have not yet been designed to handle big data or support analytics on a large scale, and the systems that are being used are often decades old.

Business intelligence tools are being used to visualize reservoir and well performance.

AI/ML methods are ideally suited for petrophysics and reservoir characterization applications that include multiple scales and types of data.

AI/ML models have been developed for the prediction of reservoir properties and performance.

Using ML techniques to quantify and analyze uncertainty has become more practical compared to using high-fidelity reservoir simulation models because of improved computational efficiency.

There is growing use of ML models for operational decision making and optimization.

One of the primary shortcomings of data-driven models is that the inner workings of these models are not well-understood in the industry because of a lack of formal training and the availability of few subject-matter experts in the workforce.

The goal of data-driven methods is not to be limited in finding structure in the data but to be able to interpret the data in terms of fundamental physical principles.

are not well-understood by most practitioners in our industry because of a lack of formal training and the availability of few subject-matter experts in the workforce. The lack of understanding results in a lack of trust in these models for decision-making purposes. Theoretical details such as the selection of the correct method, data partitioning, and error analysis (visual and quantitative) are typically overlooked. AI/ML tools are easily and freely accessible, and expertise is not typically required to apply AI/ML methods to a given data set. However, the maximum value from the models might not be obtained.

Physical inconsistencies can also result from the application of a data-driven model. When pure data-driven methods are used beyond their range of applicability to extrapolate data or in areas with sparse data, physically inconsistent results might be obtained. While the range of applicability can be limited, it is also important to ensure the results are physically meaningful, and often, pure data-driven methods are incapable of providing physical insights. The goal is not to be limited in finding structure in the data but to be able to interpret the data in terms of fundamental physical principles.

Significant advances have been made in the past few years in the areas of data analytics and modeling strategies and in their use for making reservoir engineering decisions. At a basic level, certain repetitive jobs involving data migration, event detection, and routine analysis are being automated, freeing up reservoir engineers to perform advanced analysis and interpretation. Several advanced algorithms are being developed in conjunction with reservoir physics to speed up reservoir modeling and forecasting.

Evolving and Future Needs and Expectations

Increasingly, oil and gas companies are recognizing the need to manage and store large quantities of data, which require very different solutions than those used previously. While nonrelational and cloud technologies are becoming more prevalent, there is a need for these solutions to work on more-specific oil and gas use cases. For example, time-series data are treated, processed, sampled, and retrieved very differently in oil and gas applications vs. in other industries, such as banking or healthcare. Databases are often optimized to support analytical processing and the use of ML or programming languages. Companies need to address metadata management, data governance, ML for optimization and performance management, and other aspects required for long-term strategic success. While cloud applications today are primarily characterized by lift-and-shift applications to the cloud with "best-fit" point solutions, the next-generation data management solutions will need to be natively built for the cloud platforms that can leverage the massive infrastructure.

Although business intelligence tools are used for data analysis and visualization, there are few examples of their successful integration with AI/ML-based prediction. Business intelligence and knowledge management are performed on one application, and AI/ML model training and prediction are performed on another application. A successful integration of the two can increase the value of both components. A standardized, user-centric approach to ML, which will help with user understanding, will be necessary to drive the adoption of these methods. New tools are needed that provide a what-if analysis for ML models without the need for the user to write code. The best data visualization tools will play a significant role in democratizing data and analytics, making data-driven insights accessible to users throughout an organization. Preferably, visualizations could be presented in a storytelling style to illustrate key insights.

In terms of modeling strategies, current ML methods can be mostly classified as generic algorithms, which are applied to oil and gas data. However, work is ongoing to design custom algorithms specifically for oil and gas problems. These new algorithms should be far superior to standard out-of-the-box methods for applications such as seismic processing, interpretation, and production forecasting. Various approaches have been used to integrate physics into ML algorithms (Guo et al. 2018; Molinari et al. 2019), but a new generation of algorithms is now doing it very naturally (Raissi et al. 2017). These algorithms can transition smoothly between interpolation in a data-rich environment and physics-based extrapolation when needed. This approach also has the potential to replace standard reservoir simulation solvers because it is easier to parallelize an ML algorithm than the numerical methods for partial differential equations. ML strategies based on reinforcement learning could be adapted for reservoir engineering with the inclusion of both synthetic and real data. For example, for the determination of optimal development plans or well locations, ML models could be developed in which real examples and simulation results are combined in the training.

Both data and model uncertainties need to be considered by any modeling paradigm. Several modern probabilistic ML methods for modeling and training (history matching) naturally lend themselves to multiple realizations of the same reservoir that systematically characterize posterior uncertainty (He et al. 2018).

Proven, reproducible methods are necessary for applying data analytics to reservoir engineering. Although several innovative and promising papers, books, and reports have been published, they are often cryptic or hide the key steps and the associated data sets are not provided, and as a result, the methods are not reproducible.

A new area of ML focusing on explainable AI is gaining momentum. The key objective is to produce explainable models while maintaining high accuracy,

TAKEAWAYS

Better handling of data organization and cloud applications is needed, in addition to specific data-storage solutions for oil and gas use cases.

Business intelligence tools need to be integrated with AI/ML algorithms.

User-centric visualization, preferably incorporating a storytelling style to illustrate key insights, is needed to assist human understanding.

Custom AI/ML algorithms are being developed for the oil and gas domain and should be far superior to standard methods for applications such as seismic processing, interpretation, and production forecasting.

Physical laws and relationships are being integrated into AI/ML algorithms.

Both data and model uncertainties need to be considered by any modeling paradigm.

Proven, reproducible methods are necessary for applying data analytics to reservoir engineering.

Explainable AI/ML models that maintain high accuracy are being developed.

Appropriate materials to help reservoir engineers understand analytics work products and determine their usability are urgently needed.

which would enable human users to understand, appropriately trust, and effectively manage the emerging generation of AI methods. A new set of methods in ML has been developed that provides more-meaningful insights and makes the data-driven models more transparent. Users should be able to understand why a model performed one task/computation and not another task/computation, when it succeeds or fails, when it can be trusted, and how to correct an error.

Because of the large data volumes now available, reliable analytic methods that are consistent, reproducible, and explainable are needed to help reservoir engineers perform key functions such as surveillance, reservoir management, and field optimization. There is a clear need within the industry for a technical forum to provide an exhaustive discussion of the existing, emerging, and future components of data analytics applications in reservoir technology and an urgent need for appropriate materials to help reservoir engineers understand analytics work products and determine their usability. It would be immensely helpful if fit-for-purpose training, books, technical reports, and case studies were available to practitioners. This cannot be achieved without first addressing the skills shortage among practitioners.

TAKEAWAYS

Physical laws and relationships for well-understood phenomena should be understood and honored.

The use of validation and physical consistency methods when faced with "small" data should be established as an essential practice.

Understanding of the limitations of physics-based and data-driven approaches should be emphasized.

Critical Knowledge and Experience To Be Preserved and Transferred

It is essential that data-driven conclusions preserve physical interpretability and clear relationships to well-understood phenomena. Therefore, preserving the knowledge and understanding of the physical system is important while applying the mathematical, statistical, and analytical techniques to the analysis of data. Uncertainty is a key aspect of dealing with reservoir data, and while it cannot be eliminated, it may be reduced by means of validation and physical consistency checks. This fundamental principle should be maintained, particularly when faced with "small" data. On the other hand, the notions that both physics-based and data-driven approaches have their inherent limitations and that every approach (individually or integrated) serves a purpose should be established.

Field-Scale Projects

Contributors

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Introduction

Since the discovery of the first oil and gas fields, operators have strived to optimize reservoir performance using available tools. In the past 20 years, the tools at an operator's disposal have improved significantly, and the cost of collecting and storing high-resolution reservoir performance data has been reduced significantly. The technologies involved in integrating various sources and scales of data have improved, and the prediction of reservoir performance using reservoir simulation can be accomplished quickly while incorporating fine-scale geological details and numerous reservoir and fluid-related variables.

We propose the following questions for discussion:

- How have these tools helped the modern reservoir engineer better predict future reservoir performance?
- Can the reservoir engineer of today quantify the uncertainties of future performance?
- Would the reservoir engineer of today be more confident that his or her predictions and the associated uncertainties will capture the actual reservoir performance?
- Has our ability to manage reservoirs improved, resulting in better recoveries at lower costs?
- Do we have enough data and analysis to evaluate the potential of novel development options such as carbon capture?

We need to understand the answers to these questions to better understand the technological needs of the future.

History, Background, and Original Concepts

Field management has been a consideration since the first oil field was discovered. The initial applications were based on the information that was available and the physical principles that could be applied. Even in the earliest days, it was recognized that the production from an oil field does not remain constant but declines. Initial field management practices involved the prediction of future performance by empirically fitting the historical data (crude history matching). The locations of new wells were determined first based on oil seeps and later on surface geology. The introduction of Darcy's law and accounting for multiphase flow in reservoirs provided the physical principles necessary to better manage reservoirs using production data.

Morris Muskat made the first effort to support the practice of field management with the foundations of physics. In his seminal book *Physical Principles of Oil Production* (Muskat 1949), Muskat states that "an investigation into the physics of fluid flow through oil bearing rocks yields quite definite information as to the degree to which one may successfully recover un-recovered oil and the factors influencing the recovery." Even today, this observation is valid. The purpose of field management has always been to recover "unrecovered" oil economically, and efficiently. Over time, better field management methods have evolved. We have used volumetric analysis, "zero"-dimensional equations such as material balance, decline curve analysis, analytical procedures to estimate recoveries under waterflooding, and simple procedures for estimating gas recoveries under various mechanisms. Because of the analytical nature of many of these procedures, we rarely calculated uncertainties in our estimations of remaining oil and potential recoveries.

With the introduction of reservoir simulation, our approach to field management has evolved. Although we have not abandoned the traditional, analytical approaches to capture reservoir performance and predict the future, for many reservoirs, these tools are used as complements to reservoir simulation. Reservoir simulation is a powerful tool because many of the restrictions of analytical methods are removed, such as assumptions of homogeneous properties. We also have an increased recognition that in addition to predicting future performance, we need to quantify the uncertainties associated with future performance.

The introduction of reservoir simulation introduced an additional need to collect more data so that the reservoir description—which is an input in reservoir simulation—could become more meaningful. The quality of collected data and the quality of reservoir simulation go hand in hand; the better the data quality, the better the simulation results. Over time, our ability to collect data has also improved, in two different ways: We now have higher-quality data for reservoir properties, and we have high-frequency data regarding reservoir behavior.

When we examine the history of field management, we observe that now our tools are more sophisticated, our ability to simulate complex reservoir mechanisms is much better, our data collection in terms of quality and quantity has improved significantly, and our physical understanding of reservoirs has improved. At the same time, many of the physical principles articulated by Muskat remain valid and are still used; many analytical tools still retain their importance in understanding reservoirs and predicting their performance; and a desire to use the appropriate models for specific field management questions remains strong. It is well-understood that the most-sophisticated tool is not always the best tool to optimize field management.

TAKEAWAYS

Initial field management practices involved the prediction of future performance by empirically fitting the historical data.

Muskat (1949) made the first attempt to incorporate physics into the practice of field management.

The approach to field management evolved with the introduction of reservoir simulation, and the empirical and analytical tools are now used in complement.

With the introduction of reservoir simulation, more data were needed to improve reservoir description, and higher-quality and high-frequency data are now available.

The most-sophisticated tool is not always the best tool to optimize field management.

Current Status

Historically, many reservoirs were modeled using a single description, and that description was used for reservoir management purposes. As the field management practice evolved, the importance of uncertainties in predicting future reservoir performance became better recognized.

With the improvements in our understanding of uncertainties in reservoir characterization, an increased capability of simulators to incorporate more data and significant enhancements in computational power over the past few decades have given rise to more-stochastic approaches in field-scale projects. Instead of relying on a single performance prediction, multiple future predictions are now routinely performed to quantify uncertainties in the future performance and possible outcomes.

The reservoir management of field-scale projects is being assisted by several new and evolving technologies. The principal technologies include (1) the collection and assimilation of high-frequency, high-resolution data; (2) improved modeling techniques for integrating data from various disciplines; (3) faster computers that allow the simulation of high-resolution models; and (4) improved tools for monitoring changing field behavior. The new fields have been equipped with higher-resolution-data tools, including those for both surface and subsurface data collection. The resolution of every tool has increased, providing a detailed look at reservoir properties. In some instances, the data available can become overwhelming and end up being underused. Reservoir description methodologies have made significant progress in developing assimilation tools that allow the seamless integration of geological, geophysical, and engineering data. It is not unusual to see reservoir simulations of large fields being performed using multimillion cell models that account for small-scale variations in reservoir properties.

The ability to store large quantities of data on cloud systems helps with data access, management, and reconciliation, and these systems provide almost-unlimited space for data storage/archiving. Using modern metering and gauges, the exploration and production industry is accelerating its efforts to collect data at very high frequencies; for example, it is not unusual to find data are collected at a frequency of less than 1 minute, or even on the order of seconds.

Decisions regarding the data to be collected and at what frequency are based on the biases of the

TAKEAWAYS

With the availability of robust simulators and improved understanding of uncertainties, more-stochastic approaches are being used in reservoir management decisions.

A current challenge is to determine if a benefit actually exists from recent technological advancements and the increase in data quantities and how data analytics and AI have and could accelerate the extraction of knowledge from these data.

Reservoir management is benefitting from new and evolving technologies such as improved modeling techniques that can integrate data from different disciplines and improved tools that monitor changing field behavior.

Better surveillance tools are being used to collect data at high frequencies, and the large quantities of data can be easily stored on cloud systems.

For a field-scale project to be successful, the key process is the integration and interpretation of information derived from all data sources.

An effort is underway to significantly increase the number and types of subsurface measurements.

Although large quantities of data are available, which should aid in field development and optimization, the industry is still searching for ways to cost effectively analyze these high-frequency data and use them to improve reservoir management.

technical disciplines being deployed and have a significant effect on the outcome of studies. For a field-scale project to be successful, the key process is the integration and interpretation of information derived from all data sources. This justifies spending project time on the gathering, formatting, and quality control of all data. In addition, the engagement of personnel in the production and operations groups becomes even more crucial during fast-paced developments because they are the ones who execute the placement of wells and well-completion strategies and select artificial-lift methods. They should also be actively involved in the data collection and interpretation phases of a given project.

TAKEAWAYS

An ideal field development plan requires that first-order effects be correctly identified before lower-order effects are considered.

Having a decision-making process that follows a specified workflow to identify first-order effects is important for young engineers with limited experience.

To complement the large number of surface measurements (rates, pressures, temperatures) that are available, an effort is underway to significantly increase the number and types of subsurface measurements. In unconventional reservoirs, operators collect information such as microseismic, downhole temperature sensor, and downhole acoustic sensor data at high frequencies, and these types of data sets are on the order of terabytes and even petabytes. Although large quantities of data are available, which should aid in field development and optimization, the industry is still searching for ways to cost effectively analyze these high-frequency data and use them to improve reservoir management. These high-frequency data are often qualitatively used, but rarely is an application seen where the data are used quantitatively. More collaboration between data scientists, engineers, and geoscientists is needed so that such data can be used quantitatively.

It is well-established that field developments are influenced more by large-scale features than small-scale features, which is why understanding the large-scale features is much more important. Disruptive events provide significantly more valuable information than gradual changes do. For example, knowledge that a new well drilled in a field has encountered virgin pressure is a lot more important than knowledge of the slow decline of an already producing well. A quick water breakthrough in a producing well is much more critical to understanding the reservoir connectivity than a slow increase in fractional flow is.

An ideal field development plan requires that such first-order effects be correctly identified before lower-order effects are considered. If any company has developed a systematic process where data importance and analysis are identified during field development planning, they should publish that process. Every field development study is unique, and the importance of data can vary depending on the geological environment, maturity of the field, and type of development process (primary depletion, waterflooding, enhanced oil recovery, carbon storage) that is being implemented. However, a generic description of how to identify first-order effects can be crucial in optimizing the time allocated to finish a field development study.

In many situations, however, field development involves "comfort simulation," where the decision about how to develop a field has already been made and the simulation results are used to justify the already existing plan. If indeed a "gut feeling" based on previous experience is important in making the correct decision, understanding how one arrives at that decision is critical for future field development projects. Young engineers with limited experience might not have the benefit of such experience. Thus, having a decision-making process that follows a specified workflow to identify first-order effects is important.

Evolving and Future Needs and Expectations

Recent technological advancements and the vast quantities of data now being collected should theoretically significantly increase understanding of how reservoirs behave and provide clear guidance on reservoir development. However, it is important to understand that not every newly collected data set will significantly benefit the field management process. Therefore, making judicious choices regarding which additional data to collect is also critical. Some type of cost/benefit analysis, either based on the historical performances of other fields or an analytical technique, would be useful. The next challenge is to determine how data analytics and artificial intelligence (AI) could accelerate the extraction of knowledge from these data. Simply having a very large data set available does not solve the physical challenges these reservoirs pose. Data from several disciplines will need to be combined, processed, and formatted in a manner from which knowledge can be extracted. In fact, that is the traditional "weak link" in the process: Engineers and geoscientists currently put 75–90% of their effort in a project toward data management, while most of this time is needed for the analysis, interpretation, and evaluation of such data.

In addition, a significant challenge is null or missing data, which are very common in petroleum engineering. Typical examples of null data are data that were measured but lost, data that were measured in one well but not in others, and data that are unreliable because of flaring and/or underreporting. Therefore, algorithms that can fill in the null data using physics-based assumptions need to be developed.

TAKEAWAYS

Because data quantity alone is not enough to guide reservoir development, judicious decision making regarding the additional data to be collected is critical.

Algorithms that can fill in null data using physics-based assumptions need to be developed.

Although many tools are available to integrate information at various scales, the challenge still remains to collect data that can resolve small-scale heterogeneities.

Better quantification of uncertainties in future performance prediction would improve our ability to manage reservoirs and make sound economic decisions.

Lookback studies comparing what was predicted vs. what was observed could be used to evaluate the success of new methods.

Reservoirs could be better managed if we were to have an improved understanding of the reservoir heterogeneities and important reservoir mechanisms.

Reservoir seals need to be better understood for injection processes.

Significant advances have been made in developing reservoirs to store CO_2 through carbon capture, utilization, and storage, but more understanding is needed before large aquifers could be used.

Expertise in reservoir management is needed to decide which reservoir features and behaviors are necessary inputs for the machine-learning process to predict future performance with reasonable certainty.

Although many tools have been developed to integrate information at various scales, not much has been accomplished in terms of collecting data that can resolve small-scale heterogeneities. As an example, even though simulation techniques have improved, our ability to capture hydraulic fracture characteristics in a horizontal well (e.g., the distribution and extent of natural vs. hydraulic fractures at each stage) remains limited. Even with improved tools, our challenge in the future will be to figure out how to capture small-scale details about a reservoir at subsurface conditions so that these details can be incorporated into the reservoir modeling process. High-resolution seismic and near-wellbore monitoring and measuring tools could perhaps be used to resolve such details. By combining small-scale subsurface characteristics from various disciplines into improved integrated tools, our ability to predict the future performance of a reservoir could be significantly improved.

Even though our ability to predict future performance incorporating the associated uncertainties has significantly improved, we still lack systematic processes for assessing our success in predicting future performance. That is, how well were our uncertainty predictions able to successfully capture the actual future performance? Looking back at an uncertainty prediction could guide us regarding how successful we will be in predicting future uncertainties. The goal of uncertainty prediction is twofold. First, the predicted range of uncertainty should be such that the actual performance falls between that range. Second, the uncertainty range should be as narrow as possible so that these ranges can be meaningful in making sound economic decisions. If the actual performance falls outside the range of uncertainty, clearly our ability to quantify uncertainties is not sound. If the uncertainty range is too wide, it may hamper us from making good economic decisions. We are seeing efforts in the industry to address these questions. Post-auditing—comparing the actual performance with the predicted performance—is much more common today. Because of improved computational speeds, it is possible to generate multiple history-matched reservoir descriptions, which can better quantify the uncertainties and generate predictions within reasonable ranges of the actual performance. However, currently, the history matching of multiple realizations followed by the prediction of uncertainties in future performance is mostly restricted to large multinational companies. It would be advantageous to the industry if this particular methodology became much more commonplace among companies of all sizes.

Reservoirs could be better managed if we were to have an improved understanding of the reservoir heterogeneities and important reservoir mechanisms, which drive flow behavior. For conventional reservoirs, the physics of most flow processes is well-understood; however, we need to improve our ability to gauge and quantify the interaction between reservoir heterogeneities and the flow process. For unconventional reservoirs, many uncertainties remain with respect to reservoir flow mechanisms considering that we are not even sure if Darcy's law is applicable under certain conditions.

For injection processes, the reservoir seals also need to be better understood because seal capacity affects the maximum injection rate. Better characterization of the reservoir seal should be a focus in future data acquisitions. Leveraging geologic information and advanced seismic acquisition and processing could be useful in determining the seal capacity. Time-lapse monitoring coupled with automated analysis could detect injectant pathways and identify early anomalous behavior.

Significant advances have been made in developing reservoirs to store carbon dioxide (CO_2) through carbon capture, utilization, and storage (Bryant 2007; Feder 2019). Potential storage options include depleted fields, while other opportunities exist for large aquifers. In these cases, not only do the reservoir properties need to be characterized, but an understanding of the strata above the reservoir is also required to estimate the CO_2 storage capacity. For large aquifers, before the injection of a large quantity of CO_2 could become feasible, issues such as induced seismicity, achieving solubility of CO_2, the impermeability of overlying formations, the leakage of wellbores, pressure changes in the formation, and the mineralogy of the formation and its potential for interaction with CO_2 must be better understood. These analyses will require integration between geoscience, engineering, operations, and even external stakeholders.

TAKEAWAYS

Preserving and documenting actual field examples and the lessons learned are incredibly important for future reservoir management.

The process of understanding and separating first-order effects from minor effects to make field development decisions must be documented.

Better documentation is needed regarding how high-granularity data can be properly used to improve field management.

A better understanding of which data to collect and which not to collect would be useful in improving the cost effectiveness of data collection.

Successes as well as failures should be published.

With the advances in AI and machine learning, an argument is being made that data-driven technologies can be used in place of physics-based models. In many AI applications, the general argument for their use is that we can predict future performance without understanding the physical processes. As long as large quantities of data are available and the model can be trained using large quantities of data, the argument goes that the model will be able to predict when new information is fed into it. With advances in data gathering and high-frequency information, is it possible that even reservoir management and the decision making regarding it could be accomplished using data-driven technologies? That is, if sufficient data were collected from a reservoir and the history of that reservoir as well as those of several other reservoirs could be fed into machine-learning and deep-neural-network algorithms, is it possible that the machine could predict the potential future outcome and the associated uncertainties without using physics-based models? Or, without using physics-based models, would it be difficult to capture and predict the future performance of a reservoir? Or, perhaps some combination of physics-based models and machine-learning algorithms could better predict the performance of a reservoir? These are all open questions for which we do not have answers. The application of machine learning to reservoir description and prediction has thus far provided mixed results, and success has been spotty. This could be due to the fact that without domain expertise and knowledge, machine-learning applications are hard to use. In effect, expertise in both reservoir management and machine learning is needed to understand which reservoir features are necessary inputs to correctly assess the uncertainties and predict future performance. As the application of machine-learning algorithms becomes increasingly common, these issues will come to the forefront of reservoir management.

Critical Knowledge and Experience To Be Preserved and Transferred

Hydrocarbon reservoirs are complex, and even with improved physical understanding, the large quantity of data that we typically gather still barely describes the actual nature of a reservoir. Thus, predicting future performance on the basis of limited data is only part science; it is also part art, which can only come from experience. Preserving and documenting actual field examples and the lessons learned are incredibly important for future reservoir management.

In any field management decision, the models we build are never about the truth of a reservoir. Rather, these models are simplifications or idealizations of a reservoir, but they may still be very useful for predicting future performance. Building an appropriate model requires understanding the first-order effects and ignoring second- and third-order effects. How to understand and separate the first-order effects only comes from prior experience, but we need to attempt to document such information.

Because of increased computational power and an improved ability to collect data, large quantities of data with high granularity are being collected. We need better documentation regarding how these data can be properly used to improve field management. A better understanding of which data to collect and which not to collect would also be useful in improving the cost effectiveness of data collection. Field studies documenting failures as well as successes need to be presented so that we will better understand the best practices of field management.

TAKEAWAYS

PRMS, which was initially adopted in 2007, provides a systematic framework for classifying and categorizing resources.

The 2018 updated version of PRMS provides the basis for a universal set of definitions and a classification system for petroleum resources that are used internationally for all applications.

Government regulators (e.g., US SEC) have adopted definitions inspired by PRMS.

SPE continues to disseminate information about PRMS through workshops, training courses, and supplementary documents.

Technologies for forecasting production include material balance, numerical well and reservoir simulation, RTA, and DCA.

Reserves

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Introduction

Reserves estimation and the related production forecasting technologies play dominant roles in the fate of oil and gas exploration and production (E&P) companies. Stakeholders in these companies—decision makers, investors, and reserves analysts (who most certainly include reservoir engineers)—have a huge responsibility to identify and apply the best-available practices to this work. However, "best available" does not necessarily mean "most accurate"; adequate accuracy and the timely generation of results require appropriate compromises. Maintaining and developing tools and methods that move commensurately with a rapidly changing industry knowledge base, transferring knowledge of those methods, and strengthening the confidence of those that use the reserves estimates are key goals.

> **TAKEAWAYS**
>
> Technologies for production forecasting continue to advance, led by the development of methods of specific interest in unconventional (low-permeability) reservoirs.
>
> Data analytics techniques are being increasingly applied in production forecasting.
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> Training in the latest advances in production forecasting is widely available and offered by SPE, SPEE, and their sister societies.
>
> Training in PRMS is also widely available (virtually and in person) and offered by SPE, SPEE, and their sister societies.
>
> The challenge of transferring knowledge from retiring experts to younger professionals is a front-of-mind topic.

History, Background, and Original Concepts

Effective reserves analysis and reporting require, at a minimum, the use of a system for resources classification and categorization and reliable methods to forecast the future production of resources. The system for classification and categorization has evolved into the current Petroleum Resources Management System (PRMS), which has been widely accepted globally for use in all phases of the petroleum industry. SPE led the effort to develop this system but was assisted by many other professional societies in the industry. PRMS was adopted in 2007 by SPE, the American Association of Petroleum Geologists (AAPG), the World Petroleum Council (WPC), and the Society of Petroleum Evaluation Engineers (SPEE).

SPE and its sister societies—AAPG, SPEE, WPC, the Society of Petrophysicists and Well Log Analysts (SPWLA), the Society of Exploration Geophysicists (SEG), and the European Association of Geoscientists and Engineers (EAGE)—approved in 2018 an updated version of PRMS (SPE Oil and Gas Reserves Committee 2018), which provides the basis for a universal set of definitions and a classification system for petroleum resources and is used by the industry internationally. In addition, government regulators, such as the US Securities and Exchange Commission (SEC), have adopted definitions inspired by PRMS.

Since PRMS was initially adopted by the boards of directors of SPE and the other societies, SPE has disseminated information about PRMS and the update through workshops and training courses conducted worldwide. In addition, SPE has recorded a web-based series of training lectures for transmission to SPE sections, individuals, and reserves stakeholders throughout the world, even in remote locations. SPE committees are currently working on supplementary documents, including an update to the 2011 PRMS applications guidance document and a new "examples" document.

Production forecasting, which provides the basis for reserves estimation, comprises a group of technologies almost as old as the petroleum industry itself, yet new technologies and approaches continue to add to the tool kit estimators can deploy. Common forecasting methods include production decline curve analysis (DCA), rate transient analysis (RTA), material-balance analysis, conventional gas and black-oil reservoir simulation, and compositional simulation for near-critical fluids, while storage and transport simulations in nanopores (such as in shale reservoirs) are being developed (SPEE 2016).

Current Status

Technology related to reserves estimation and evaluation has continued to advance, although much work remains to be done. Primary evolving technologies include RTA, reservoir simulation (Jones et al. 2016; Moinfar et al. 2016), and DCA (SPEE 2016). Low-permeability reservoirs have provided myriad opportunities to advance the technology of reserves estimation and analysis. The inclusion of modern and maturing data analytics techniques is becoming a common methodology within workflows for estimating and projecting reserves production.

SPE and its sister societies, particularly SPEE, have provided training globally on production forecasting technologies. Production forecasting methods—including but not limited to data analytics, machine learning, and enhancements of more-mature technologies—continue to be featured in technical journals and at technical conferences and workshops. In addition, SPE and other organizations continue to conduct training throughout the world in the application and use of PRMS.

It is also recognized that the industry is on the cusp of a transition, with a significant portion of the current workforce aging out through retirement in the coming decade. This challenge of transferring accumulated knowledge is a front-of-mind topic in all areas of the industry, and no less in the field of reserves and resources estimation.

Evolving and Future Needs and Expectations

While the system for resources management (PRMS) has progressed to a high level, continued diligence will be necessary to respond to changes in the industry and to improve the external understanding of the reliability and integrity of resources estimates (Olsen et al. 2011).

E&P companies have been criticized recently (particularly by the investment community) for their optimistic and overconfident estimates of ultimate recovery in low-permeability resources, such as shales (Miller et al. 2017; Elliott 2019; Matthews et al. 2019; Olson et al. 2019). The criticisms included but were not limited to (1) the improper application of traditional DCA methodology, especially in the choice and application of Arps *b*-factors during transitional and transient flow and in the application of terminal decline rates; (2) the improper construction and application of typical-well production profiles (i.e., type wells or type curves); (3) an improper or a lack of application of uncertainty analysis; (4) a failure to account for well-to-well interference in forecasting; and (5) a failure to account for the negative impact of multiphase flow (e.g., gas/oil, gas/oil/water). Confronting these criticisms and improving the methods applied are challenges that must be addressed.

Potential solutions will include an improvement in the understanding and proper application of the familiar Arps method. However, additional methods should also be improved and more broadly applied, such as the incorporation of simulation modeling earlier in the process of evaluation and RTA where applicable (Collins and Ilk 2015).

The dominant method for forecasting in ultralow-permeability reservoirs remains production DCA. Although many replacements for the Arps decline model have been suggested, none have proved to be significantly more reliable for forecasting. Nevertheless, much remains to be learned about the proper application of the Arps model and similar decline models for forecasting in reservoirs with limited production histories and with expected future complications such as multiphase flow, well interference, and pressure-dependent formation and completion properties.

Full-physics simulation models (including storage and transport in nanopores) are evolving for use in longer-term forecasting for ultratight reservoirs, and they may be approaching the commercial-application stage (Baek and Akkutlu 2019). These models will be useful for calibrating and applying rapid but approximate empirical and analytical models that are based on simplifying assumptions. However, understanding how to apply the results of this type of forecasting to a categorization of reserves will have to progress in accordance with these methods. In general, an earlier application of simulation modeling could be beneficial, despite the obvious caveats and uncertainties inherent in early application.

TAKEAWAYS

PRMS (as curated by SPE and associated professional groups) must be continuously reviewed for potential updates and modernization.

Advances in production forecasting should be applied to improve forecasts and enhance credibility with the investment community. Forecasting needs to go beyond the unquestioning reliance on the traditional Arps hyperbolic decline model.

Improvement in the construction and application of more-reliable typical-well production profiles (i.e., type wells or type curves) is also essential for credibility with investors.

Production forecast and reserve estimation methods, such as DCA and RTA, need further improvements to be used for multiphase flow, well interference, and pressure-dependent formation and completion properties.

The development (and earlier application) of full-physics simulation models for forecasting in unconventional reservoirs is required for longer-term forecasts.

The industry, with SPE as a key player, will be called on to develop better training programs that incorporate a recognizable purpose and applications.

The experience and knowledge of the soon-to-be-retiring professionals will be important resources to capture while they are still available.

RTA as a technology for forecasting and reserves estimation is mature in its development. However, it faces challenges in modeling multiphase flow, including gas/oil flow in retrograde-gas reservoirs, oil/gas flow in volatile-oil reservoirs, and gas/oil/water flow in other reservoirs (Moinfar et al. 2016). The basic approach has been to adapt analytical solutions for single-phase flow to more-complex multiphase flow situations using pseudofunctions. However, practical problems that need to be overcome include obtaining trustworthy reservoir description data, such as relative permeability relations, for use in these pseudofunctions.

A broad challenge in production forecasting and reserves estimation in both conventional and unconventional reservoirs is the lack of consistent knowledge regarding the application of currently known recommended practices, as lacking in rigor as they may be. This problem is easy to state but more difficult to resolve. The industry will need to do a better job of informing practicing reserves analysts and reservoir engineers about the strengths and limitations of currently available approaches. This could be accomplished by enhancing our efforts to educate (rather than simply train) users to comply with regulations, forecast with acceptable accuracy, and estimate reserves in ways that provide confidence to all stakeholders in petroleum E&P. The SPE training courses, for example, reach only a small fraction of practicing engineers, and the reasons for this might include the cost and travel difficulties, and perhaps even indifference. The industry, and SPE in particular, may be called on to broaden its training outlets (in person and virtually), provide cost offsets (such as free courses and scholarships), and add cohesion and purpose to the training structure to make the training more inviting to and useful for a broader population.

TAKEAWAYS

Resources classifications and definitions, and how to apply principles in specific situations, are key elements of the reserves-estimation practice.

The specific methodologies used in production forecasting and reserves estimations should always be presented and taught with the underlying concepts, assumptions, and limitations.

Methods and best practices of estimating reserves deterministically and probabilistically should be documented.

Regardless of whether deterministic or probabilistic methods are used in resource evaluation, the importance of assessing uncertainty should be emphasized.

The exiting of experienced professionals from the industry because of retirements will only add to the challenge of disseminating accumulated knowledge gained through experience. However, as the daily work responsibilities of these retiring professionals lessen, there will be opportunities to support and incentivize mentoring and direct knowledge transfer (such as through courses, conference speakers, and in-house corporate training) using this great source of experience.

Critical Knowledge and Experience To Be Preserved and Transferred

Resources classifications and definitions are fundamental, but as history has taught, they must be carefully tended and supported without pause. Beyond just the learning of definitions, the application of theory and constructs is always important. Experience cultivates skill in applying learned principles, and the dissemination of those learnings will be imperative.

Preserving the concepts underlying the applications of specific methodologies in a reserves analysis is an area in which professional societies can play a vital role. In the case of petroleum reserves estimation, SPE and associated industry groups should be leaders in accumulating and distributing the underlying knowledge required.

This will span the range of quantification methods, including both deterministic and probabilistic approaches. The key to both method types is the proper assessment of uncertainty. Whether the uncertainty is stochastic or scenario-based, an evaluator will need the tools to assess the uncertainty involved regarding the inputs as well as the outputs (SPEE 2010; McLane and Gouveia 2015).

The key to any estimate of resources is a time-based forecast of those volumes. The economic viability, capital allocation, and future profitability of resources, fields, and companies rely on the reasonable accuracy of such forecasts. This applies to conventional and unconventional resources, with each subject to specific complexities. The beneficial effects of collective knowledge and experience can be used to instill awareness of both the appropriate application and the limitations of a given method of forecasting resources.

Project Economics

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Introduction

The availability of inexpensive and reliable energy has been an important driver for the economic growth and wealth of nations around the world. Fossil fuels—including coal, oil, and natural gas—have been the key energy resources supporting the unprecedented transformation of civilization since the 18th century.

The global macroeconomic environment for energy has changed significantly over the past 15 years. The unconventional revolution in the US and the discovery of vast natural-gas resources around the world have had far-reaching implications for geopolitics, energy commodity prices, and the transport and flow patterns of energy commodities worldwide. Additionally, the dramatic change in supply and demand fundamentals, increased public awareness of climate change, and interest in alternative energy sources have affected capital markets and the investor appetite for oil and gas.

The tools used in economic evaluation and decision making are outside the scope of this green paper, and the technical data used in project economics have been covered in previous sections. Rather, this section discusses the macroeconomic environment affecting oil and gas projects. It is intended to bring closure to the green paper by underscoring the ultimate objective of all reservoir activities and highlighting the importance of socioeconomic and political conditions in what is typically considered to be a purely technical field.

TAKEAWAYS

Global political and socioeconomic instability influences commodity prices and therefore energy economics.

Until recently, global supply was heavily influenced by OPEC and the national oil companies of its member states. Demand growth was centered in developed economies.

An era of hydrocarbon scarcity—when it was believed that global oil and gas reserves were being exhausted faster than they could be replaced—existed for decades and ended in the early 2000s. This dynamic drove investment decisions, the valuation of companies, and energy policy.

History, Background, and Original Concepts

The precarious stability of energy economics, with its strong interdependence on global political and socioeconomic stability, has made predicting and planning for the future an almost-daunting task. Because of this difficulty, energy economists have developed tools to guide energy investments and resource development strategies at the company and national levels.

It should be noted that until recently, the following market dynamics prevailed:

- Global energy markets and prices were largely controlled by OPEC and its bigger producers.
- The global spare supply capacity, or the supply available to backstop short-term growth or unplanned outages, was primarily held by OPEC.

- Supply was sourced from conventional reservoirs, and projects consisted of long lead-time investments requiring significant capital. Exploration efforts were risky and often unsuccessful.
- Until the early 2000s, it was thought that global oil reserves were being exhausted faster than they could be replaced and the market was running out of oil and gas; the reaching of peak oil was believed to be imminent.
- New global supply discoveries were dominated by major oil companies or national oil companies instead of small or independent operators.
- Demand growth was primarily occurring in developed economies.
- Economic growth and low-cost energy were encouraged over the minimization of climate and environmental impacts. In addition, the climate impact was not fully understood or widely accepted.

Current Status

The US unconventional revolution has had one of the greatest impacts on the energy industry so far this century. In less than 15 years, between 2005 and 2020, US crude and condensate production grew from 5 million B/D to more than 10 million B/D (US Energy Information Administration 2021). (However, this number is significantly less than the observed peak in November 2019 of 12.966 million B/D and reflects the crude production drop caused by the COVID-19 pandemic crude market collapse.) During the same period, gross natural-gas production grew from 55 Bcf/D to more than 104 Bcf/D (US Energy Information Administration 2021). Because this production growth far outpaced domestic demand growth, the US is now a net exporter of natural gas, crude/condensate, and natural gas liquids (also referred to as liquid petroleum products). The year 2020 will be notable for the significant upheaval in oil and gas markets. Both the severe reduction of demand because of COVID-19 and the price wars have

TAKEAWAYS

Between 2005 and 2020, US crude and condensate and gross natural-gas production doubled, and the US is now a net exporter of natural gas, crude-oil/condensate, and natural gas liquids.

Growth in supply, the development of new resources, and the relatively less growth in demand have resulted in a dramatic drop in prices, leading us into the current era of abundance.

Because of persistent low prices, investors have shifted their focus from growth to demonstrating capital efficiency, scrutinizing balance sheets, and demanding a return on capital.

Investment is now being affected by concerns about climate change and policies generally supportive of renewable energy.

DCF models are the standard method for evaluating project economics and benchmarking assets.

In the current market, investors expect E&P operators to generate free cash flow and generate strong full cycle and corporate returns.

Private companies must build businesses focusing on cash-flow growth.

Global producers will need to invest in both unconventional and conventional resources, creating both opportunities and risks.

Several factors must be considered for each project when designing a company strategy or portfolio mix, including operational experience, political risks, and expected future commodity prices.

collapsed prices and changed supply and demand levels in the short to medium term. However, the longer-term dynamics presented in this section will likely prevail.

Coinciding with the growth of US production in the past 15 years, significant conventional natural-gas resources were discovered and developed around the world, in Qatar and Australia, for example, with more planned projects underway. This growth in supply, the development of new resources, and the relatively less growth in demand have resulted in a dramatic drop in the price for crude, natural gas, and natural gas liquids, and we are now in a time period that is often referred to as the "era of abundance."

This era of abundance has also resulted in a significant paradigm shift in the way oil and gas are valued by investors. When the market believed that the world was running out of hydrocarbon resources, investors thought that commodity prices would trend up over time as the cheaper resources were exhausted and the use of new, more-expensive resources became necessary. This resulted in both public and private investors encouraging exploration and production (E&P) operators to increase production volumes, often by taking on debt to fund that growth. However, now that low prices have persisted for more than 10 years for natural gas and more than 6 years for crude/condensate, investors have shifted their focus from growth to demonstrating capital efficiency, scrutinizing balance sheets, and demanding a return on capital.

The investor appetite for oil and gas has also been affected by concerns about climate change and the growth of renewable energy. The importance of this change to capital markets and the investment landscape cannot be overemphasized; however, it must also be noted that capital markets, like commodity markets, are cyclical, and the most-important factor that drives investors is returns, which are largely a function of commodity prices. An improvement in commodity prices would increase returns, improve the balance sheets of E&P operators, and result in additional oil and gas fields beginning to generate profits. As a result of price increases from the 2020 lows and conservative capital-expenditure programs, many US producers have reported improved balance sheets and financial metrics. In addition to commodity price increases, technological advancements and changing geopolitical dynamics promise to reshape oil and gas markets in the future.

While the macroeconomic environment for energy continues to evolve, the fundamental valuation methodologies for both conventionals and unconventionals have not changed. The most-common method to construct realistic and accurate valuations is the discounted cash flow (DCF) model (Reynolds 1959). When a decision involves buying, selling, or funding an asset through external means, a market-based approach can also provide a relative value of the asset on the basis of how investors price similar assets. The typical thought process underlying petroleum valuations includes the following:

- To value an existing asset for internal purposes: What is the value of my asset?
- To value an asset's reserves for external reporting purposes (e.g., to the US Securities and Exchange Commission): How will investors value my asset?
- To value an operational decision: Should I perform this operation?
- To value an asset under consideration for acquisition: Should I buy?
- To value an asset under consideration for disposition: Should I sell?
- To value a funding decision: How much should I invest and at what structure?

Conventional assets generally take longer to develop and by nature are less flexible, thus allowing for less responsiveness to variations in commodity prices. There are fewer companies around the world with the scale and access to capital required to bring a conventional project to life, and those companies are often either national oil companies or major global companies.

For conventional reservoirs, multiyear reservoir characterization, subsurface and surface modeling, history-matching, and simulation studies are typically undertaken to estimate original hydrocarbons-in-place, predict well performance, and eventually estimate the value of the asset. The fundamental reservoir engineering applications are still valid in the valuation of conventional assets. However, with the advancement of high-performance computing and real-time access to operational data, asset valuations are more dynamic than ever.

Unconventional assets, by nature, contain more geologic variation, even within a basin or play, and therefore vary in terms of volume predictability and economics. For more than a decade, public upstream companies meaningfully outspent their cash flows as they explored shales. Their primary focus was on production growth and long-term inventory life rather than generating free cash flow. During this time, private operators invested minimal capital to delineate acreage to prepare for asset divesture. However, the upstream business model has rapidly changed since the COVID-19-related downturn. In the current market, investors expect E&P operators to generate free cash flow and strong full cycle and corporate returns. Private companies are expected to do more than "prove and flip." For private companies to find their exit, they also focus on building businesses focusing on cash-flow growth. This requires that private operators take a full-field development approach instead of operating under a minimal delineation program. For the first time, there is a common strategy regarding the allocation of capital to develop these reservoirs regardless of whether the company is public or privately held.

For unconventional assets, the most-common building block of DCF models is single-well economics, which can then be aggregated into a full development model to value an asset within a company or value an entire company. This approach worked well early in the unconventional era. With approximately 150,000 horizontal wells drilled in unconventional plays to date according to state and federal regulatory filings and drilling permits, the industry has realized that every well is unique and many variables can influence well performance and economics. The role of technology and big data is now more important than ever because optimizing field development is an extremely complex issue given the interaction of reservoir quality, stacked development, completion techniques, operational procedures, spacing, and timing. With operators in development mode, the intrinsic value of every asset hinges on the operator's strategic approach to pad, cube, staggered, and sectional planning/execution and managing parent/child issues. A comprehensive subsurface analysis is required to accurately predict well and field performance and characterize future inventory. Without the correct engineering and geoscience tools and approaches, the industry is inevitably at risk of overestimating or underestimating the productivity of such reservoirs, which is ultimately what drives asset valuation and project economics.

The strategy of oil and gas producers and their portfolio-construction decisions have evolved in recent years alongside the US unconventional revolution. There are now two distinct types of investments: lower-capital unconventional onshore wells that take less than 30 days to drill and can be brought online within months and more-capital-intensive conventional projects that require years to discover, test, and finally bring online. Additionally, investors can balance their portfolios from a commodity perspective and select oil, gas, or a combination.

Unconventional assets are unlikely to ever meet ongoing energy needs. The lower overall volume growth rate in the US simply means the US supply will not be sufficient on its own to balance the market. Therefore, global oil and gas producers will need to invest in both unconventional and conventional resources in the future. These two competing investment types will create both opportunities and risks for national oil companies, major global oil companies, and shale producers as they define their own strategies and construct their portfolios.

Today and going forward, most major oil companies are investing in both unconventional and conventional projects all over the world, while some are leaving the space and focusing only on the transition to alternative energy sources. There are also independent unconventional operators in the US that have taken positions in conventional projects abroad, primarily in natural gas. In addition, many companies have diversified and are concurrently investing in multiple unconventional and conventional projects.

Several key factors must be considered for each project when designing a company strategy or portfolio mix, including

- Technical and operational experience
- Political and business risk in a specific region or country
- Workforce and labor accessibility in a specific region or country
- Expected future commodity prices
- Desired commodities mix exposure
- Land or acreage position
- Midstream and downstream infrastructure required to produce assets and the ability to integrate the business to mitigate risks
- Ability to account for unforeseen occurrences, such as COVID-19 and the Macondo blowout and explosion
- Environmental, social, and governance (ESG) and other nonfinancial metrics demanded by investors and shareholders
- Competing energy sources to meet net-zero goals or emissions reductions

It is important to note that much of what has been discussed thus far applies to both unconventional and conventional projects, but the scale, risks, and timelines are often different.

Evolving and Future Needs and Expectations

Going forward, there are several key market dynamics to watch that will drive prices and, therefore, the investor appetite for oil and gas.

The first is demand growth trends for crude and natural gas. Because it is unclear if or when demand will return to pre-COVID-19 levels, this topic is under debate. Air-travel demand has improved since 2020, but it is expected that it will take years to reach pre-pandemic levels, and global macroeconomic growth is being challenged. Transportation fuel represents the largest component of crude demand, and the growth of electric vehicles will influence this demand in the future. How much demand for refined products will be displaced and when?

The longevity of US unconventional resources will remain a key factor in overall commodity flow patterns and prices. Specifically, how long can US production continue to grow, in what quantity, and at what price? This is notwithstanding the current shorter- and medium-term impacts resulting from COVID-19 and the subsequent price collapse.

Growth in renewables, particularly in developing nations where the majority of increased demand for hydrocarbons is expected to come from, should also be monitored. This growth will largely be sponsored by government policies that provide tax incentives, mandate certain infrastructure retirements, and further incentivize investment. Where and when will renewables grow as a percentage of the energy mix? How competitive from a returns perspective could renewables be as policies evolve, consumer preferences change, and costs begin to affect the general public?

In addition, cheaper and longer-lasting batteries are being developed all around the world, and the required breakthroughs in physical chemistry are a question of when, not if. There is also growing investment in and operational activity surrounding carbon capture, utilization, and storage (CCUS) as policy-driven incentives are increasing globally to achieve net-zero goals by 2050.

Geopolitics, trade wars, and currency wars also influence the market. Shortages in crude/condensate supply are common and often a result of political unrest, attacks on infrastructure, or economic instability. Trade and currency wars have increased over the past several years, and each event has had far-reaching impacts on the price of commodities and demand. Where and when will these events happen in the future? And how often?

TAKEAWAYS

Demand growth trends for both oil and gas will be closely tracked and analyzed.

The longevity of and ultimately the appetite for investment in US unconventional production resources will remain a key factor in overall commodity flow patterns and prices.

The growth in renewables, particularly in developing nations, should be monitored.

Technological advancements in the areas of battery technology and carbon capture are being researched around the world.

Geopolitical risks and socioeconomic volatility will continue to influence the market.

The final market dynamic to watch is the continued investment and research in EOR in both the Middle East and unconventional plays.

Before 2010, OPEC was a key driver of supply and price, but the group's price-setting ability has been hampered in the current era of fundamental oversupply of crude/condensate, led by supply growth in non-OPEC countries. The pandemic forced significant cuts in the production levels of OPEC and their partners, along with those of other non-OPEC nations around the world. Large quantities of crude remain on the sidelines, and the timing of the return of this supply is uncertain.

The final market dynamic to watch is the continued investment and research in enhanced oil recovery (EOR) in both the Middle East and unconventional plays, as well as the success of carbon dioxide EOR projects as part of CCUS initiatives supported by tax incentives. Will supply increase because of technological advancements in EOR, and how will the decarbonization of the upstream industry by means of CCUS affect the longevity of oil and gas production?

Critical Knowledge and Experience To Be Preserved and Transferred

The valuation methodologies and technical approach used in project economics have not changed. DCF models are and will remain the standard methodology for evaluating projects quantitatively, although ESG metrics are now also being used to benchmark and compare projects. Successful energy projects rely on an integrated approach between technical/operational and commercial teams, and financial drivers, optimal drilling/completion/production techniques, and intangible factors like ESG must be considered to maximize project economics.

Thus, while the fundamentals of project economics have not changed, it is important to note how global and local energy market dynamics, investor appetite, and the volatility/cyclical nature of commodity prices drive investment decisions and will continue to do so. Global market dynamics are continuously evolving as a result of macroeconomics, energy-transition initiatives, energy investments, asset valuations of unconventionals vs. conventionals, and portfolio constructions. The current era of abundance has resulted in a significant paradigm shift in the way oil and gas are valued by investors, and the sustained drop in commodity prices as a result of the new lower marginal cost of supply has forced a change in the capital markets that cannot be overstated.

Investors now require capital discipline, pressure operators to generate free cash flow, and emphasize returns on investment, and these changes are significant and here to stay. In addition to the market changes already observed, investments in technologies like EOR in both conventional and unconventional plays and in new regions like the Middle East will continue, the market share from renewables as energy sources will continue to grow, and concerns about climate change will continue to reshape markets and influence commodity prices. In addition, the technological innovations that unlocked unconventional resources and fundamentally changed oil and gas markets are now being developed for technologies such as carbon capture and batteries.

TAKEAWAYS

DCF models are and will remain the standard methodology for evaluating projects quantitatively, although ESG metrics are now also being used.

Successful energy projects rely on an integrated approach between technical/operational and commercial teams, and several factors must be considered to maximize project economics.

While the fundamentals of project economics have not changed, global and local energy market dynamics, investor appetite, and the volatility/cyclical nature of commodity prices will continue to drive investment decisions.

The current era of abundance has resulted in a significant paradigm shift in the way oil and gas are valued by investors, and the sustained drop in commodity prices has forced a change in the capital markets that cannot be overstated.

The energy market continues to evolve, and changes resulting from renewables, climate change concerns, and technological innovations should be expected.

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