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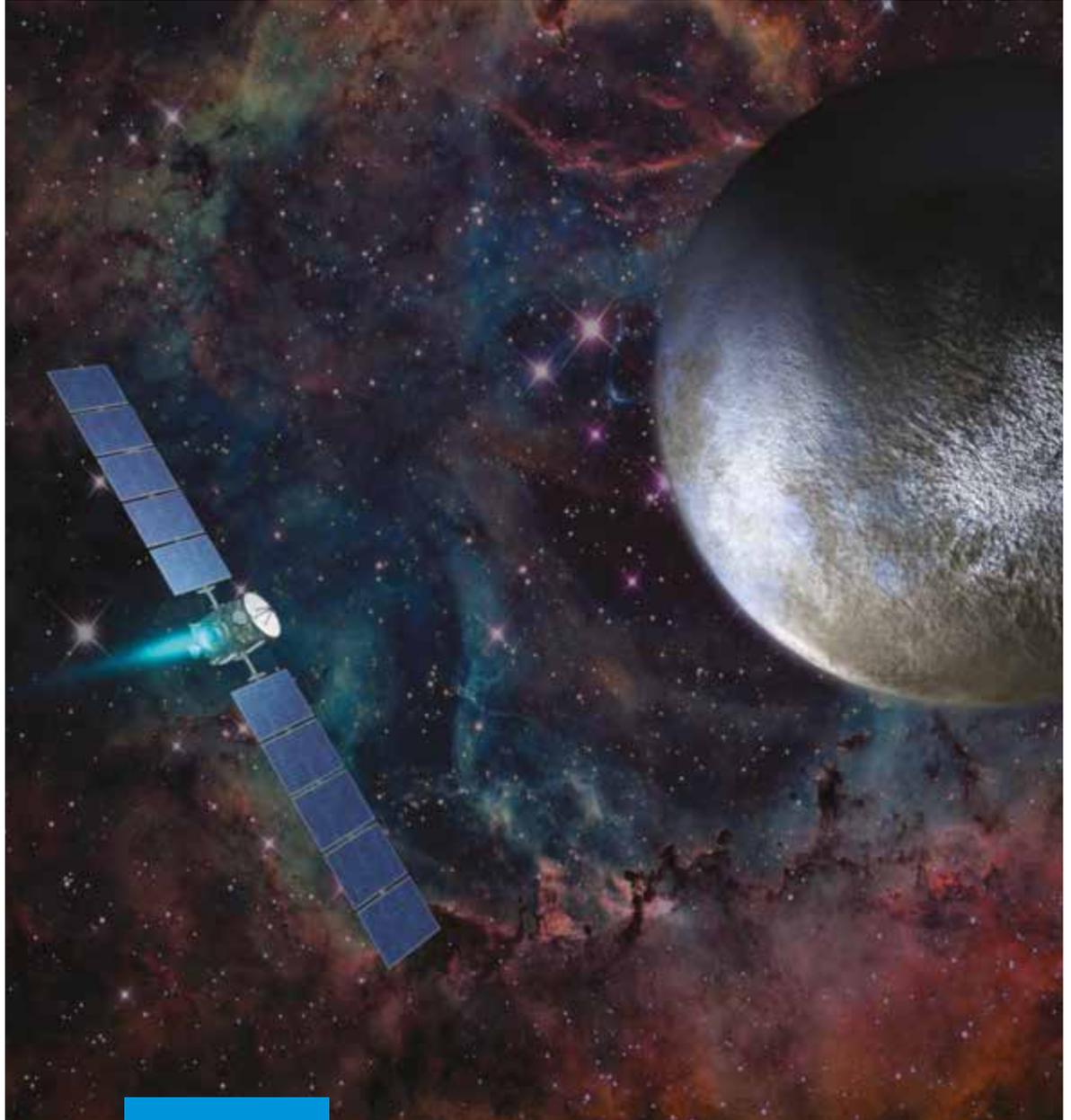
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Machine learning for the upstream industry

Data-driven solutions using AI and machine learning can have a significant impact on oil and gas operations upstream, explains *Shahab Mohaghegh*, Professor of Petroleum and Natural Gas Engineering, West Virginia University, and Head of Intelligent Solutions.

The data revolution is hard to ignore in today's world. The impact of data and data-driven solutions in our everyday lives and its contribution to success of some of the largest high-tech enterprises makes this game-changing and disruptive technology ever more visible. The realisation that data can and must be treated as an indispensable asset in the upstream oil and gas industry is rapidly growing. But how can an upstream organisation benefit from this technology and what is the path to its adoption?

Disruptive technology

Data-driven analytics is an integrated technology unifying multiple disciplines. Both IT and engineering play significant roles in its functionalities. Database, statistics, machine learning, and pattern recognition are among the most important technologies that need to be well understood to take maximum advantage of data-driven solutions. When contemplating adoption of this technology the most common mistakes made by E&P companies are:

- Hiring generic data scientists (ie statisticians and AI experts with no background in

petroleum engineering and geosciences) to build data-driven expertise in their organisations.

- Using the services of start-ups with minimal proven domain expertise to identify a problem by looking at their data and offer a solution.

The correct approach is to require domain experts in your organisation to demand a solution to a specific (non-trivial) problem and to define the criteria for success ahead of the implementation.

Incorporation of data and data-driven solutions into an upstream oil and gas organisation requires significant cultural adjustment. The new technology must demonstrate that it can solve problems more efficiently, with less uncertainty, less effort, and with higher impact on the bottom line. Application of data-driven analytics in our industry is not as new as some may think. The Society of Petroleum Engineer's *Journal of Petroleum Technology* published a series of three articles on artificial intelligence and its potential in the upstream petroleum industry in 2000.¹

Data-driven analytics have already made important

contributions to the oil and gas industry. In situations where our understanding of the physics is still in the developmental phase and the number of unknowns are overwhelming (such as production from shale), data-driven analytics have proven to be valuable in understanding the complex nature of the production process, helping optimise completion design and production. Some operators are taking advantage of existing data-driven know-how in the industry while others are contemplating the possibilities, and yet others have gone astray with disappointing outcomes. Data-driven analytics have resulted in applications that have been dubbed as 'too good to be true' by some engineers that have seen the results. Here are a few examples.

Drilling and NPT reduction

Maintaining wellbore stability, monitoring and managing drilling non-productive time (NPT) are key factors in improving safety and drilling efficiency while minimising the costs associated with problems during well construction and production operations. Despite the need to understand the conditions which create drilling operation risks such as wellbore instabilities,

there is no industry consensus regarding which stability analysis methodologies are most applicable under varying geological and operational conditions.

Using machine learning we have been able to train, calibrate and validate models that use real-time measurement while drilling (MWD) and logging while drilling (LWD) in order to predict NPT tens of feet ahead of the bit during the active drilling (bit on-bottom) process. The model has been validated using data from offshore platforms in the North Sea. Furthermore, predictive models were developed and validated using blind wells to predict NPT tens of minutes ahead of time during the tripping and reaming (bit off-bottom) process in shale assets in North America.

Reservoir modelling

Data-driven reservoir modelling (also known as top-down modelling or TDM) is an alternative (or a complement) to numerical simulation. TDM uses machine learning and data mining in order to develop (train, calibrate, and validate) full field reservoir models based on field measurements (facts) rather than mathematical formulation of our current understanding of the physics of fluid flow through porous media.

Unlike other empirical technologies that curve fit production (ie decline curve analysis, DCA), or only use production/injection data for its analysis (ie the capacitance resistance model, CRM), TDM integrates all field measurements such as well construction, completions and stimulations, well logs, core data, well tests, seismic, along with production/injection history (including wellhead/bottomhole pressure and choke setting) into a cohesive, comprehensive, and full field reservoir model using artificial intelligence technologies. TDM is an empirical full field model where production (including the gas-oil ratio (GOR) and water cut (WC)) from every individual well is conditioned to all measured reservoir characteristics and operational constraints. TDM matches the historical production (validated through blind history matching) and is capable of forecasting the future behaviour of wells and fields.

Reservoir management

Numerical reservoir simulation and modelling is a computationally expensive technology. Traditional proxy models sacrifice either

physics or resolution in space and time in order to address the extensive computational footprint of numerical simulation. Data-driven smart proxies take advantage of the 'big data' solutions (machine learning and pattern recognition) to develop replicas of the numerical models that are highly accurate, but have very fast response time. Smart proxies honour the complete physics and offer high resolution in space and time. The Surrogate Reservoir Model (SRM) is Intelligent Solution's (ISI) implementation of smart proxy for numerical reservoir simulation.

Field tested against most popular numerical reservoir simulators, SRM is capable of replicating the results of multi-million cell reservoir simulation models with high accuracy in seconds.

Production optimisation

Coupling of hydraulic fractures and natural fracture networks and their integration and interaction with the shale matrix remains the major challenge in reservoir simulation and modelling of shale formations. After spending hundreds of millions of dollars the industry is coming to the conclusion that conventional technologies such as decline curves, rate transient analysis or numerical simulation fall short in providing value to production from shale.

Data-driven analytics has proven to be far more applicable than the conventional techniques in modelling production from shale. It has helped engineers to discover hidden patterns in the production and to build and validate predictive models that condition production from shale wells to reservoir and completion characteristics. Anadarko Petroleum, for example, has been using ISI's data-driven analytics in its unconventional operations. Data-driven analytics is now being used to selected candidate wells for re-fracs.

Some confusion

Amongst the enthusiasts of this new data-driven analytics technology, the overlap between IT with engineering and geosciences has caused some confusion. Attempts to clarify such confusion have resulted in two separate SPE Technical Sections – the Digital Energy Technical Section which is mostly concerned with IT, and the Petroleum Driven Analytics Technical Section which is concerned with aspects

of engineering and geosciences. Each section is dedicated to certain aspects of data in everyday operations. But some confusion still remains.

Furthermore, despite the mountains of evidence and historical debate, there are still those that believe data-driven analytics that is largely based on machine learning and pattern recognition (mostly developed since the mid-1980s) is the same as traditional statistics. They fail to recognise the fundamental and philosophical differences between these disciplines. Hopefully, as data-driven analytics becomes more popular in our industry, these confusions will be minimised.

Petroleum data science

The term 'data science' generally refers to skills acquired by scientists with a background in statistics, machine learning and data mining. However, experience has shown that minimal impact can be expected when pure data scientists are hired by oil and gas operating companies.

For data scientists to be successful in such circumstances massive patience is required from management – a phenomenon that has been scarce in our industry! The successful alternative is to train (or hire) a 'petroleum data scientist' from within the organisation with experience in drilling, reservoir engineering or production and a strong enthusiasm (and/or background) in the art and science of data-driven analytics.

Path to adoption

There are two components to the adoption of data-driven analytics in the oil and gas industry. Operators can either develop their own solutions or outsource their data-driven solutions. Developing an in-house solution will require patience and considerable amount of resources while outsourcing can bring quick results that can justify future in-house development. ●

¹Virtual Intelligence Applications in Petroleum Engineering: Part 1; Artificial Neural Networks. Part 2; Evolutionary Computing. Part 3; Fuzzy Logic'. *SPE Journal of Petroleum Technology*, Distinguished Author Series, September, October, November 2000.