Digital Oil Field: Online management of the oil and gas asset lifecycle

Introduction

The oil and gas industry has recently begun to adopt and leverage standards and best practices from other industries with capital and risk intensive asset lifecycles. The intersection of advances and capability maturity in the areas of Big Data and predictive analytics are resulting in measurable benefits, especially for operators of large offshore projects with long asset lifecycles.

Data and Asset Lifecycles

Many large international offshore operators have enterprise level asset lifecycle processes that recognize the need for online tracking of the data, information, knowledge, and business intelligence that supports key decisions. Most of these online systems track key milestones and “stage gates” from exploration through abandonment.

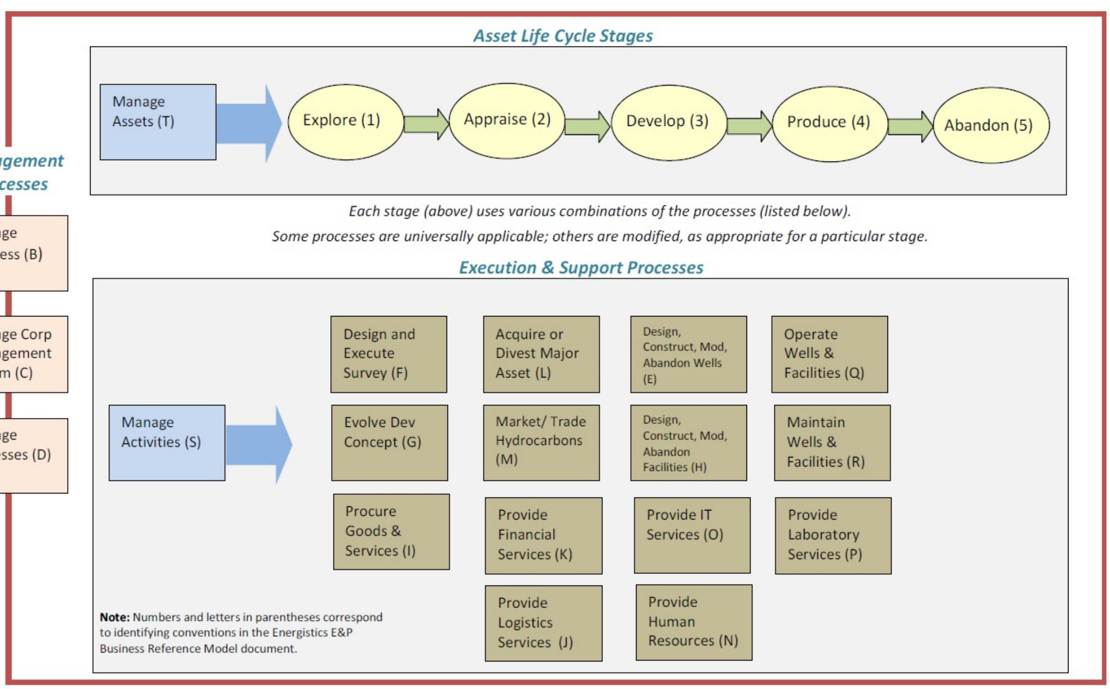

Fig 1. An exploration and production Business Process Reference Model to support online asset management. Copyright Energistics, 2014, all rights reserved. Used by permission

Note that in this standard business reference model, providing Information Technology (IT) services is one of the key execution and support processes at each stage. The identifying conventions for IT include the provision of applications and databases for asset lifecycle maintenance.

Recently, there has been interest in how applying online predictive analytic techniques might improve the efficiency of these processes and give organisations a competitive advantage in the next cycle of lower commodity prices. This interest has coincided with an understanding of the business case for using what is now known as Big Data, and with the acceptance of methodologies for applying predictive analytics to asset management. With the release in 2014 of ISO 55000, an international standard for asset management, there are now agreed principles and terminologies that can be applied to measure progress with offshore oil and gas assets and benchmark against other industries (ISO, 2014). This standard provides a definition of predictive capabilities, as opposed to preventative or corrective, that allows the industry to measure capability maturity on a standard scale for the digital aspects of offshore assets (Davey et al, 2014). In understanding capabilities for online management of asset lifecycles, organisations must be prepared to evaluate a range of facets that can be grouped into the general categories of people, information, systems, and processes. It is important to remember that several industry studies have shown that among these, data and information are consistently rated as the most important factor (up to 38%) in understanding of subsurface risk factors that impact performance of complex assets (CDA, 2011).

Big Data and Predictive Analytics

Some common characteristics make oil and gas asset lifecycle management comparable to other capital intensive industries and able to benefit from the application of standard processes. One is the critical role of data and technology in opening new opportunities and driving the profitability of assets in the face of fluctuating commodity prices, and the importance of an organisation's agility in transforming information into insight (Glenn, 2009). Another is the sheer volume of data created by offshore oil and gas operations. Oil and gas has worked with data volumes in the multiple petabyte range for over a decade, and has also had the requisite facets of velocity and variety to make it one of the first verifiable producers and consumers of Big Data (Vesset et al, 2012). Other factors driving both the value of predictive data analytics and the adoption of standards around it are the prevalence of mergers and acquisition activity in the oil and gas industry (Deloitte & Touche, 2012), and the level of government regulation (IQ Business Group, 2014), with energy ranking in the top 3 in each category. Yet the oil and gas industry has been perceived to be slower than others in demonstrating, publishing and sharing the financial benefits that can be derived from online predictive analytics, which are reported to be as high as incremental returns on investment of 241 percent (Nucleus Research, 2012). While some research indicates that this reluctance is the result of innovations being held by oil and gas service providers (Perrons, 2013), we present here some recent evidence of publically available examples of the value of predictive analytics in the asset lifecycle.

Predictive analytics in oil and gas can be viewed as the next step in the evolution of data management capability maturity models, moving up the value chain from data. At each step in the capability maturity model, value is added and deleterious elements are removed. This is accomplished by applying capabilities and by managing unique facets of Big Data for oil and gas. In the latest model (Evans and Kozman, 2014), capability maturity is measured against the complexity of an organization to understand benchmarking and impact on financial performance. The complexity of the intelligence used for predictive analytics can be quantitatively measured with industry standard IT tools and processes that capture four important and unique aspects of oil and gas Big Data. These are referred to in the industry as the four "P's", proliferation, propagation, pervasiveness and persistence. Each of these digital facets is a unique multiplicative combination of the traditional and accepted three "V's" of Big Data but is created by the unique usages and business cases for predictive analytics in oil and gas offshore operations.

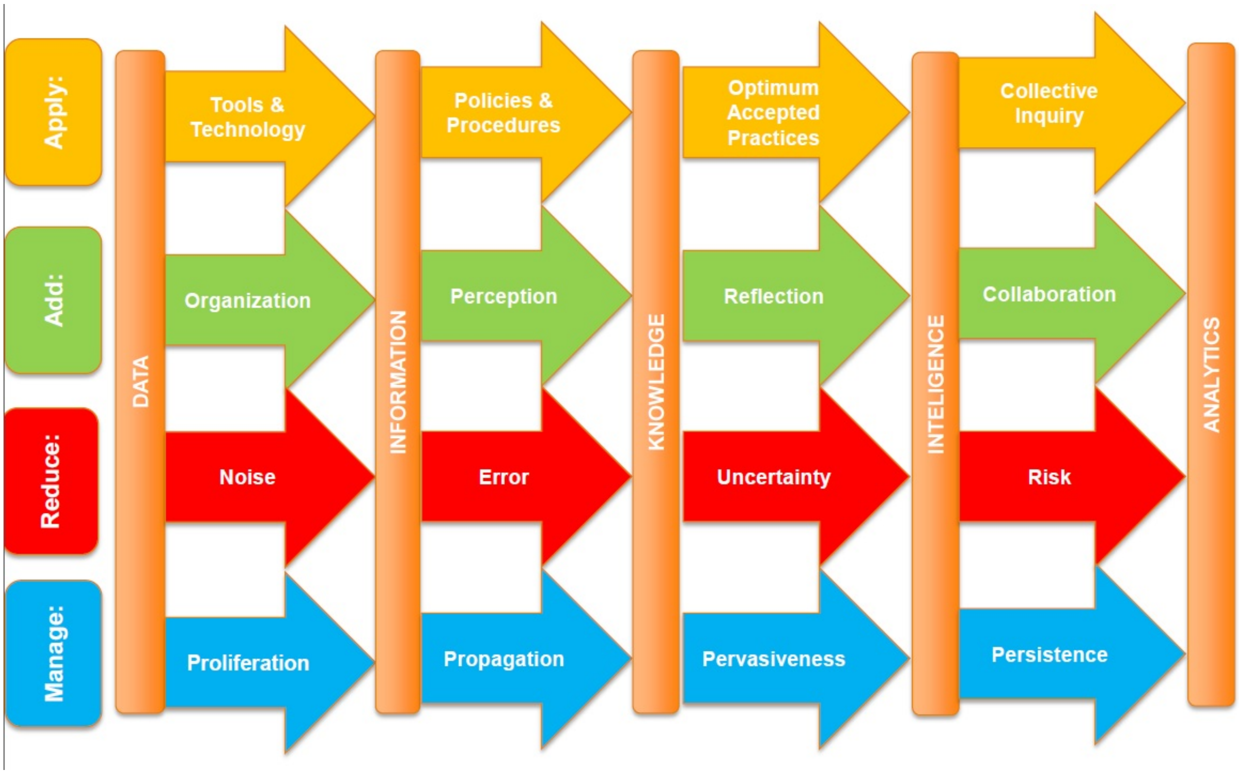

Fig. 2. The relationship between organisational maturity levels and the capabilities and digital facets required to achieve them. Adapted from http://en.wikipedia.org/wiki/DIKW_Pyramid, after Solien, M., Green, A.R., and White, L.P., 2003, American Association of Petroleum Geologists International Conference, Barcelona, Spain

Proliferation results from the rapid multiplication of data in specialized tools with potentially contradictory interpretations. It is measured by the "churn rate" on data storage systems, or the percentage of data that is created, read, updated or deleted on storage systems over time. The proliferation of data creates information, but it also introduces noise into the system, which must be reduced through the application of organizational structures and the use of specialized tools and technology. Propagation is the product of distribution and duplication of information by iterative workflows in disparate disciplines. Its defining metric is a combination of variety and volume, and it can be measured by looking at the duplication of data files across storage areas managed by different functional silos in the organization. Propagation introduces some perception into information in the form of knowledge, but it also introduces sources of error that must be managed with standardized processes and procedures. Pervasiveness describes how knowledge expands to fill the available storage space through probabilistic and statistical realizations and heuristics. While necessary to create actionable business intelligence through reflection on the value of knowledge, this process also introduces a measurable level of uncertainty which becomes a business critical piece of metadata to be managed with optimum accepted practices. Pervasiveness can be measured by the time taken for different formats of the same information to appear on a storage system in multiple working versions and scenarios. Finally, persistence is the characteristic value of intelligence over the decadal and generational life spans of offshore oil and gas assets. This value is derived through collaborative and collective inquiry to reduce risk, and it is this value that can be measured by the results of a successful predictive analytics implementation. Demonstrated metrics for this characteristic can be obtained by analyzing the frequency, duration, and repeatability of data access across between disciplines and functions, and over time.

Business and Use Cases

The value of predictive analytics has been recently demonstrated through application to the large volume of maintenance and performance data available from offshore equipment. It has been repeatedly shown that surface equipment failure contributes to more non-productive time on offshore rigs than any other cause (SAS, 2014) including subsurface geologic risk, and the rapidly expanding volume of data available from online sensors on that equipment can yield insights and predictive capabilities that improve considerably on either equipment vendor provided maintenance schedules or strictly reactive thresholds and alarms. Case studies have shown that critical equipment failures can be predicted between as much as 72 hours to 8 days before the event with suitable historical input to artificial neural networks (Kozman, 2014) and for items such as electric submersible pumps (Brule and Fair, 2014). This success would allow reductions in workover costs of as much as 4%, for a return on investment of over USD$20 million per year.

Fig.3. Online display of precursor events to an electric submersible pump failure. While these events would not have triggered static threshold alarms set by the equipment manufacturers, predictive analytics and the output of an artificial neural network were able to use this intelligence to successfully predict the failure. (Data courtesy of APO Offshore, used by permission).

Further use of the same techniques has been demonstrated to be able to predict nitrogen oxide (NOX) emission levels from offshore power generation equipment in order to proactively keep them below environmental regulatory levels and avoid operating fines, and the system has been recommended for predictive capabilities around hydrate formation in subsea flow lines and stress on offshore mooring lines. Recently a business case has been built to use predictive analytics in the monitoring and control of chemical injection for pipelines. In this application, the optimum dosage of corrosion inhibitor is calculated based on the actual pipeline flow rate to control costs and guarantee integrity and safety.

Other recent developments of online predictive analytics for the digital oilfield have focused on monitoring combinations of drill string vibration amplitudes and frequencies, mud pit volumes, rock sample pyrolysis and cuttings, hydrogen sulfide levels, overpull and underpull, pore pressure and drilling trajectory in order to optimize drilling penetration rates and avoid instability and failure (Bhandari, 2012).

At a recent workshop sponsored by the SPE Petroleum Data-Driven Analytics Committee on Decision Making and Value Delivery, several vendors noted recent progress in using holistic predictive analytics to predict and avoid stuck pipe problems while drilling, with resulting decreases in problems that account for up to 20% of non-productive time on rigs and over USD$2 billion in losses to the industry (Priyadarshy, 2014).

Other operators have expressed interest in improving reliability in digital oilfield applications by using online monitoring of chemical injection skids and sample tracking to reduce downtime due to chemical injection, reduce reprocessing of products that are out of specification, and ultimately reduce operational costs by factors of between USD$1 and 10 million per year.

References:

The following Energistics (c) products were used in the creation of this work: Energistics, 2009: “E&P Business Process Reference Model”, Version 2.0, December 2009, http://www.energistics.org/Assets/bprefmodeldocumentfinaldec09.pdf

Bhandari, A., 2012,”Drilling & Production Data Repository & Analytics for E&P; Memory Based Reasoning Techniques for Predictive Safety and Analytics”, PointCross Inc. White Paper, 2-Jul-2012, http://pointcross.com/docs/E&P%20Data%20Repository%20for%20Analytics.pdf, retrieved 29-Dec-2014, used with permission.

Brulé, M.R. and Fair, Jr., W.B., “Fusion of Empirics and Physics Boosts Predictive Analytics”, SPE Workshop—Petroleum Data-Driven Analytics: Decision Making and Value Delivery, November 19-20, 2014, Galveston Texas, U.S.A., http://www.spe.org/events/14agal/documents/14AGAL-Technical-Program.pdf

Common Data Access, Oil and Gas U.K., 2011 “Data Management Value Study”, April 2011, http://www.oilandgasuk.co.uk/knowledgecentre/DataManagementValueStudy.cfm

Davey, M., Dohr, L., Durga, A., Elias, M., Kompella, K., Lipsey, D., and Regli, T., “Digital Asset Management Maturity Model Enables Audit, Improvement of Digital Asset Management Capabilities”, October 2014, Digital Asset Management Foundation, The DAM Maturity Model Version 2.1 http://dammaturitymodel.org

Deloitte & Touche, 2014, “M&A Trends Report 2014”, May 1 2014, http://www2.deloitte.com/content/dam/Deloitte/us/Documents/MA/us_ma_deloitte_ma_trends_full_report_2014_052814.pdf

Evans, E. and Kozman, J., 2014, “Using Business Intelligence Maturity to Survive Change”, SMi's 15th annual E&P Information and Data Management Conference, 6th February to 7th February 2013, London, United Kingdom http://www.ndbteam.com/media/2488/bim5_history_and_background_update_2014_v2_4.pdf

Glenn, M., 2009, “Organisational Agility; How business can survive and thrive in turbulent times”, EMC Economist Intelligence Unit, March 2009, http://www.emc.com/collateral/leadership/organisational-agility-230309.pdf

IQ Business Group, 2014, “Highly Regulated Industries”, IQ Business Group Technical Center of Excellence, http://iqbginc.com/clients/highly-regulated-industries

ISO, 2014: “Asset management -- Overview, principles and terminology”, International Organisation for Standardisation, http://www.iso.org/iso/catalogue_detail?csnumber=55088

Kozman, J., 2014, “Predictive Analytics for Asset Optimisation”, UNI Strategic 2nd Annual Next Generation Digital Oilfields Conference, Kuala Lumpur, Malaysia, November 2014 and SPE Singapore section Technical Presentation, 8-jan-2015. https://www.facebook.com/SPESingapore?fref=ts

Nucleus Research, 2012, “The Big Returns from Big Data”, Research Report M20, April 2012, https://nucleusresearch.com/research/single/the-big-returns-from-big-data/

Perrons, R.K., 2013, “How Does Innovation Happen in the Upstream Oil and Gas Industry? Insights From a Global Survey”, DOI http://dx.doi.org/10.2118/166084-MSDocument IDSPE-166084-MS Publisher Society of Petroleum Engineers Source SPE Annual Technical Conference and Exhibition, 30 September-2013 October, New Orleans, Louisiana, USA Publication Date2013 Document Type: Conference PaperLanguage: English ISBN978-1-61399-240-1 Copyright 2013, Society of Petroleum Engineers. https://www.onepetro.org/conference-paper/SPE-166084-MS

Priyadarshy, Dr. S., 2014, “Leveraging Big Data Explosion in Oil and Gas Industry: A Paradigm Shift is Needed to Remain Competitive”, Society of Petroleum Engineers, Petroleum Data-Driven Analytics Workshop, Decision Making and Value Delivery, 18-19 November, 2014, Galveston, Texas, U.S.A., http://www.spe.org/events/14agal/

SAS, 2014, “How do we improve drilling efficiency and predict events that adversely affect safety and cost – in near-real time?”, SAS Oil and Gas Solution Brief, http://www.sas.com/content/dam/SAS/en_us/doc/solutionbrief/oil-and-gas-improve-drilling-efficiency-106477.pdf

Solien, M., Green, A.R., and White, L.P., 2003, “Human Technology: Leadership in the Application of Intellect”, American Association of Petroleum Geologists International Conference, Barcelona, Spain, Management Forum: People, Technology, and Data - What it Takes to Get Ahead in the E & P Game

Vesset, D., Woo, B., Morris, H.D., Villars, R.L., Little, G., Bozman, J.S., Borovick, L., Olofson, C.W., Feldman, S., Conway, S., Eastwood, M.,Yezhkova, N., 2012, “Market Analysis: Worldwide Big Data Technology and Services 2012-2015 Forecast”, IDC March 2012, http://www.idc.com/research/viewtoc.jsp?containerId=233485

Authors:

Jess Kozman, Chief Technology Officer, APO Offshore, jkozman@apooffshore.com

Carol Piovesan, Chief Executive Officer, APO Offshore, cpiovesan@apooffshore.com