Embracing the Digital Twin for E&P

AN IENERGY® EBOOK
Working Towards a Digital Twin for E&P

As the E&P industry adjusts to the new economic climate and the lower price of oil, organizations are confronted by the pressing need to lower costs and increase efficiency. Therefore, the digital transformation of the E&P industry has become an imperative if companies are to survive and succeed in this digital era.

This digital transformation is multifaceted and includes cloud technology, automation, artificial intelligence and machine learning. One very important concept that is gaining momentum is the application of digital twins across the E&P lifecycles. The ability to have a digital representation of the various operations allows the industry to test and model multiple scenarios before committing resources to building a physical twin. This approach, therefore, can help to cut costs and increase efficiency.

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Digital Transformation in E&P, therefore, requires more than launching new technologies, products and innovations. As oil and gas cautiously embraces digital transformation, the industry must evaluate where and how disruptive technologies can be applied in order to “go digital.” Where can advanced analytics, big data, machine learning, artificial intelligence, automation, robotics, cloud, and software platforms be applied for exploration, drilling and production workflows? Where do operators begin, what application areas should they focus on, and what are the pitfalls to avoid?

The core mission of the E&P industry does not change with digital transformation. But transformation requires a rethink of the business model, which capabilities are critical, which are commoditized; and it most certainly requires crafting a strategy rooted in asset intimacy — while staying rooted to the core business: hydrocarbon recovery with health and safety.

Digital solutions in E&P require asset intimacy, edge intelligence combined with advanced technologies such as machine learning and artificial intelligence:

» Integration of smart, connected assets at the edge with their digital twin
» Integration of historical, real time and modeling into actionable insights

Digital transformation in E&P is not simply replacing pen and paper with digital information, cataloging data, or applying new technologies to old tools and processes. Digital transformation entails a redefinition of boundaries, a re-evaluation of the standard business model and a fundamental shift underpinned by technology disruption, creating new sources of value, and new advantages. In E&P this transformation has implications in the use of digital technologies to drive new processes, workflows and operating models. It requires bridging the physical world, such as assets, machinery, sensors, tooling with digital technologies, such as cloud, advanced technologies, data driven models to identify and unlock value, drive efficiencies, and redefine traditional boundaries of collaboration across the E&P value chain.

The concept of a digital twin in asset intensive industries is a revolutionary framework for replicating and modeling physical assets in the digital world, leveraging data and inputs from modeling and real-world operations, and creating a continuous feedback

INTRODUCTION
Industries in virtually every vertical market are facing the reality of a digital transformation. They are asking themselves how they will survive and succeed in the digital world, what strategies they will pursue, and how to avoid traps and pitfalls in their transformation journey.

‘Digital’ as a term appears to be over-hyped and over-used because digital terminology, use cases, examples, and do’s and don’ts are everywhere. On the other hand, there are real use cases of where industry boundaries are being redefined, and existing and new businesses are facing a new reality based on digital transformation, such as in media, entertainment, hospitality, and transportation. However, for asset intensive industries of exploration and production (E&P), aviation, heavy equipment, and others, digital transformation is a more complex and daunting journey. E&P, for example, faces a unique set of challenges: large capital expenditures, distributed operations, labor intensity, remote operations, longer innovation cycles, regulation, health and safety are a few.
loop between the physical and digital. The digital twin represents the physical asset, and as operations continue and more data is generated, it is continuously updated with greater historical insights that improve the simulation, generating better inputs for the asset. Both the physical asset and the digital model are continuously changing and improving.

BUILDING BLOCKS FOR E&P DIGITAL SOLUTIONS

The E&P industry has a rich history of innovation across exploration, drilling, and production. Successive waves of innovations in surveying, drilling, data capture and processing, 3D reservoir modeling, horizontal drilling, and well technologies, as well as improvements in health and safety, have contributed to increased efficiency and higher recovery of hydrocarbons with fewer resources at lower costs. Any type of E&P digital transformation involves the same fundamental digital building blocks. While E&P companies, regions and asset-types each have a unique digital transformation journey, a common technical and business blueprint underpins the digital solution throughout the E&P lifecycle. This blueprint, called the Enterprise Architecture, must be clearly defined and executed on.

The concept of a digital twin in asset intensive industries is a revolutionary framework for replicating and modeling the physical asset(s) in the digital world, leveraging data and inputs from the modeling and real-world operations, and creating a continuous feedback loop between the physical and digital.

Smart, Sensing and Connected Hardware

E&P and other asset intensive industries are rooted in physical equipment, tools, and machinery, among others. Horizontal drilling, rotary steerable technologies, rotary drill bits, hydraulic fracturing and a host of other innovations have made possible higher recoveries with lower cost, improved safety and greater efficiencies. Oil and gas innovations have been paralleled with innovations in sensors, actuators, control systems and other embedded technologies which make hardware “smart”, more sensing and more connected. This has been made possible with higher sensor densities, lower power consumption, advances in widespread connectivity, such as Wi-Fi, Bluetooth, ZigBee and LPWAN. The variety and volume of information that can now be collected is magnitudes greater than in years past. In short, physical equipment and assets are becoming smarter and more connected. In a digital landscape, these hardware assets can be geographically distributed, continuously or intermittently connected, generate information at different rates, of different types, and have open or proprietary protocols controlling them. The Digital Enterprise Architecture at Halliburton provides primitive data types that enable these smart, sensing assets to be connected to each other through a common platform – DecisionSpace® Platform – and enabling insights to be derived from the information generated by the assets. The volume of real-time data often multiplies with automation. For true digital value to be derived, data from smart hardware must be transformed into insights, and those in turn drive feedback to the hardware, (such as anticipate through sensors, react through actuators, and model through data).

Data and Digital Information

Data is the bedrock for E&P operations, and digital transformation initiatives amplify the relevance of information and data management. Exploration, planning, design, modeling, drilling and completions – all require quality data from connected operations. Quality data is imperative for evidence-based decision making in E&P, as connectivity and automation allow for the automated execution of tasks and the transfer of control to machines. With smart, sensing hardware and automation, data often grows at hyper-exponential rates. New data adds to the massive volumes; some many decades old, stored in data warehouses, dark storage, tapes and now more than ever in cloud environments.

An architectural approach to digital data, including but not limited to data storage, access, loading, transfer, search, and quality, is a pre-requisite without which the fidelity of the digital twin is compromised. How can one handle digital data and continue to derive insights in real-time, and what technical and business capabilities are required? Data lakes (as complements or replacements for data warehouses) have been proposed to handle scale, performance and costs, and can be very effective for petro-technical digital solutions; they can handle multiple data types from a wide variety of sources, deal with E&P-scale data volumes and simplify development of analytical models; and data does not need conversion to a schema and queries often need not be pre-defined. The DecisionSpace Platform works seamlessly with data-lake architectures and has pre-defined E&P primitives for seismic, exploration, drilling, production and real-time data.

Differentiators for Digital Transformation:

- Asset intimacy through smart, sensing hardware; edge intelligence; machine learning; connectivity and data
- Open, end-to-end enterprise architecture created especially for E&P
- E&P digital solutions across exploration, drilling and production

Based on powerful distributed computing technologies for storage, compute and visualization, DecisionSpace Platform simplifies the development and on-boarding of digital solutions, including real-time data streaming, 3D/3D visualization, and big-data and machine-learning based applications. Real-time, sensor, machine data, drilling, field, production and back-office data processing scales with an in-memory distributed file system, and digital applications can be deployed on premise or in the cloud, with best-ofbreed security (and provenance). What differentiates the DecisionSpace Platform from a generic industrial IoT platform is the ability for digital solutions to plug-and-play and scale with an E&P platform. Persistent distributed data management for well-logs, for seismic (trace-based, bricked, and long-term seismic), for historical structured and unstructured exploration data (e.g., from Neftex® Insights), for drilling and production, and real-time sensor data is architected from the ground up. Refactoring a generic IoT platform for E&P could suffer in performance, scale, cost and time to value.

Edge Intelligence

Successive generations of computing technologies have moved between two fundamental paradigms: centralized versus distributed. From mainframe computing (centralized) to client-server (distributed) to mobile-cloud (centralized), there is an increasing shift to edge computing (distributed). Physical assets (trucks, machinery, heavy equipment, oil rigs, home thermostats, cars, cameras etc.) are examples of edge devices that are becoming more “intelligent”; i.e., they are capable of decision-making, analytics, and insights that can be generated and processed within the edge device itself (without the need for an external resource). In the oil and gas industry, the drive towards edge intelligence is driven by four fundamental factors:

- Geography: remote operations: Faster and more accurate decisions are best made closest to the edge, where assets reside. With powerful smart, sensing and connected hardware, and increased connectivity and data insights, the edge can make decisions – and may not always need to connect to a central office for all decision-making.
- Economics: What can be done at the edge economically (embedded sensors, analytics etc.) does not require expensive data transport and processing remotely. This has significant implications when dealing with large data volumes and complex assets.
- Regulation: All raw data no longer needs to be moved, can be processed remotely and archived. Data does not have to cross territorial boundaries. This has historically been a huge barrier to faster decision-making in oil and gas. With edge-intelligence, this hurdle is vastly simplified.
- Security: Greater controls, audits and checks can be assured when data is not moved. Only meta-data or aggregate insights may need to be accessed. This assures a higher degree of increases, data privacy and regulatory compliance.

The edge is evolving fast, with rapid innovations from technologies such as Intel Compute Stick™, Omega2®, PocketChip™. These technologies provide a level of edge programmability that was not possible before. Remote operations in drilling, deep water, and in harsh environments, will see an increasing use of powerful edge computing, where the power of smart, sensing hardware generated data is combined with intelligence at the edge to deliver insights right where they are needed. Drilling outputs can be processed, fed back to the controls, and corrections made to drilling paths, geosteering or for corrective actions during NPT. Voice of the Oilfield™ solution by Halliburton is an example of a digital solution where smart, sensing hardware combined with data and edge intelligence is seen in action. Down-hole surface instrumentation (from Halliburton and non-Halliburton hardware),

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combined with edge analytics, workflow orchestration (on DecisionSpace Platform) and the Halliburton DecisionSpace Production 365 solution, delivers real-time insights through a digital twin model. The Voice of the Oilfield digital solution enables continuous reservoir optimization linking predictive maintenance, edge analytics, well performance evaluation, surface network optimization, subsurface optimization, and economic analysis in a continuous loop through a physical-digital representation.

Machine Learning, AI and Advanced Technologies

While digital has the potential to unleash unlimited data streams, it also provides unprecedented opportunities to capture, analyze and transform raw data into insights with automation. Machine-learning, artificial intelligence (AI) and other advanced technologies (Neural nets, Bayesian learning etc.) hold tremendous promise in E&P. The Halliburton Big Data and Data Science Center of Excellence has developed patented and advanced capabilities across multiple problem areas. Data science can be used across exploration, drilling, production workflows – each with their own objective functions. Pattern matching for faults drilling, production workflows – each with their own objective functions. Pattern matching for faults.

Digital holds promise for transforming the E&P industry with new tools, capabilities, and processes to impact business outcomes – helping to reduce costs, improve efficiencies, improve safety, and increase predictability of outcomes. But digital brings challenges: it can level the playing field much faster, turn partners into competitors, redraw competitive boundaries and erode long-standing advantages. In the race to digital, asset intimacy, innovating fast and partnering with the right vendors are critical to driving successful outcomes.

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DecisionSpace Platform leverages open, modern computing technologies (Apache Spark™, Apache Storm™, Kafka™) and has tuned these technologies for E&P applications and workflows. For example, scale and availability is provided through both traditional and NoSQL databases such as Apache Cassandra™ and Hadoop®, elasticity and flexibility through on-premise, private (Landmark Earth™), and public cloud support through AWS”, “Azure” etc. A powerful microservices architecture allows existing and new applications from operators, partners, 3rd party ISVs) to plug-and-play with the DecisionSpace® Platform. E&P applications, many written over time, can leverage the API (application programming interface) architecture and do not need to be rewritten.

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INTRODUCTION

While the aviation, aerospace, and renewable energy industries have experienced enormous benefits over the past decade, the adoption of data-driven and/or physics-based reduced-order models as a digital twin is still in its infancy in the oil and gas (O&G) industry. Benefits captured across these other industries include: improved quality and speed of decision-making, greater asset utilization, condition-based monitoring and prognostication, enhanced operational-efficiency and improvements in preventive maintenance. However, many challenges exist in our industry with respect to the generation and adoption of data science principles for the creation of a digital twin. We tend to rely more on physics-based models. Moreover, key gaps exist in the understanding of basic principles concerning how and when to use different data-analytics tools to create a virtual representation from data, and then combining it with trusted physic-based modeling; thereby, allowing the assimilation of data-driven models into physics-based models. Computational modeling techniques have existed for decades, and commodity-level accessibility and availability of high-performance computing and software tools has allowed for their widespread acceptance. Practicing engineers in
our industry have been able to leverage this accessibility, making new levels of analysis a reality in O&G applications (e.g., fluid-structure interaction (FSI), vortex-induced vibration, hydrate formation, slug control and erosion and corrosion estimation). This was made possible due to hardware enhancements (e.g., multi-core GPUs and CPUs) and the use of scalable infrastructures, such as the cloud and high-performance clusters. While these attributes have made it easier to simulate complex physics in O&G applications, its Achilles heel is the time and expense of running these simulations. This is compounded by the many unknowns associated with downhole actual data and the slow pulse rate to the surface.

Therefore, incorporating physics coupled to a data-driven digital twin (hybrid digital twin) is required to improve accuracy, cost effectiveness and efficiency.

The concept of a digital twin as a virtual representation of what has been manufactured was originally defined in the context of Product Lifecycle Management. The idea consisted of comparing a digital twin to its engineering representation of what has been manufactured versus what was designed. However, this representation has grown to include many flavors of the digital twin:

- **Digital Twin Instance (DTI):** A specific physical instance of an asset
- **Digital Twin Aggregate (DTA):** An aggregation of multiple DTIs
- **Digital Twin Environment (DTE):** Integrates multi-domain physics for a variety of objectives

The digital twin could be used for predicting future behavior and performance of the physical asset. A natural progression of this theme is the digital twin for System of Systems thinking (e.g., DSoS) – the coupling of digital twins that allows for interoperability and emergent behavior (DSoSI).

**THE HYBRID DIGITAL TWIN**

The ultimate goal of the digital twin for any industry, but especially O&G, is for operators, service and logistic companies to benefit from data-driven and/or physics-based solutions. Data-driven analytics and numerical/analytical expressions create a reduced-order model, which generates the digital twin; however, individually, they have limitations that need to be addressed prior to application in the field.

The hybrid digital twin continuously learns and updates itself from multiple sources to reflect their near- or real-time status and working condition. This learning digital twin adapts using sensor data that conveys various aspects of its operating conditions, from similar fleets of assets or from larger systems and its environment, which it may be interacting with and/or comprised of.

What is a Hybrid Twin and how is it generated?

The underlying predictions from physics-based models are beholden to the assumptions made a priori, and thus accuracy and uncertainty may be suspect unless validation and quantification can be performed. Data-driven models, on the other hand, are largely based on machine-learning techniques. The predictive accuracy of these models is determined by the quality of the data and incorporates no physics to provide meaningful insight. Hence, the creation of an adaptive digital twin based on a data-driven approach with the insightful attributes of physics-based understanding will enable more accurate and valuable predictions. The adaptive nature of the hybrid twin provides significant benefits and advantages during well construction and production planning, where variations between wells and fields are the norm.

Digital twins can be created using several routes, with high-fidelity numerical analyses being one such avenue. These results must undergo a dimensionality reduction from 4D/3D to a reduced-order model executable digital twin that provides speed and efficiency to quickly quantify the performance envelope of a physical asset or process. The speed and adaptive characteristics of the digital twin allow many more system configuration analyses against the objective in near- or real-time mode.
What are the characteristics and importance of digital twins? Table 1 shows each digital twin, along with their characteristics, as represented by a potential mathematical expression, as well as their pros and cons. In essence, the hybrid model incorporates the physics that govern the phenomena being observed with the accuracy typically associated with these fundamental principles. The addition of a real-time data-driven model synthesized into the physics model (or vice-versa) adds greater confidence and tenability in the underlying predictions. It’s important to note that physics models are routinely based on engineering assumptions and validated on limited data sets. This is overcome by the data-driven models. Since both these types are mathematically reduced-order and complement each other, the computational expense of hardware is minimized and speed to convergence is increased. It’s these characteristics that add considerable economic value to our customer in terms of worker safety, health and higher engineering efficiency. Further importance can be demonstrated with an industry example as it relates to a real-world application; namely, multi-phase fluid flow in pipelines.

COMMERCIAL USE CASE – MULTI-PHASE MODELING IN PIPELINES
Multiphase flow in pipelines has garnered tremendous interest in the oil and gas industry, and extensive modeling capital has been spent on gaining an understanding of the phenomena that drives this complex flow. Specific focus has centered on drilling and production applications (e.g., Fluent™ and CFX™ from ANSYS, STAR-CCM+™ from Cd-Adapco and numerical 1D codes from OLGA and LEDAFLOW). Distinct approaches to steady-state (SS) multiphase flow systems include:

- **Homogeneous flow models:** Two phases traveling at the same velocity and, thus, the flow can be reduced to a single-phase flow.
- **Phase-slip models:** Phases assumed to be traveling at different velocities.
- **Multi-fluid models:** Interactions between the two phases described in separate conservation equations written for each phase.
- **Detail flow models:** In contrast to the above models, two or three dimensions usually involved to describe the flow field.
- **Transient Reduced-Order:** SS mechanistic models in conjunction with single-phase flow.

Meziou et al. (3) presented reduced-order models for transient two-phase gas-liquid flow in pipelines. The proposed model is comprised of an SS multi-phase flow mechanistic model in series with a transient single-phase flow model in pipelines. The authors followed a three-step process for the transient modeling: 1) use of a mechanistic SS model to determine the flow pattern, SS liquid hold-up and pressure drop, 2) calculation of equivalent fluid properties (e.g., bulk modulus, density, speed of sound and viscosity), and 3) use of a dissipative, distributed-parameter model (referred to in the literature as "the exact model") for laminar flow modeling.

An expression for the turbulent distributed parameter model included a lumped turbulent resistance introduced at the end of the pipeline.

The researchers state that the main benefit of the developed reduced-order model was the reduced computational burden of estimating transient multi-phase flow in pipelines; thereby,
enabling real-time estimation of pressure and flow rate. The alternative to the above expression is to solve the Navier-Stokes equations simultaneously for all phases present in the pipeline (such as oil, water, and gas). As shown by the first row in Table 1, they can be obtained by averaging the corresponding transient 3D laminar or turbulent model equations in the lubrication approximation. This would involve five continuity equations (such as oil, gas, water, and oil and water droplets), along with three momentum equations for oil, water, and the combination of gas with liquid droplets. If we make the assumption that all phases are isothermal, then one energy equation is solved. This results in a system of nine conservation equations and one equation of state to be solved. Depending on the complexity of the problem and the required accuracy, an appropriate time-step and special discretization scheme can be used. The alternative is to run very costly 3D/4D CFD numerical code that can simulate the full-field flow physics, but requires significant investment in both hardware and time.

CONCLUSION
Computational hardware and sophisticated software tools have been tremendously improved in the past several decades, allowing complex multiphysics phenomena to be simulated more accurately. Yet, the computational cost needed to obtain these results, depending on the size and complexity of the simulations, can be prohibitive. The advent of reduced-order models helps to alleviate the cost barriers associated with higher-dimensional/high-fidelity simulations. One option to create data-driven models is to utilize machine-learning analytic algorithms. However, this can potentially lower accuracy due to data quality issues and the exclusion of the underlying physics that governs the observed phenomena. The use of neural networks (NNs) is quite fashionable today, but consists only of data-driven formulations. NNs can currently only comprehend data; therefore, they cannot learn the true physics behind the data. Eventually, NNs must comprehend both data and physics to facilitate increased accuracy. This will lead to widespread impact to the engineering and data science communities, which will fundamentally change the conventional approach to the methodology of model training. This path will make NNs smarter and significantly contribute to the field of artificial intelligence (AI). Automation will be impacted appreciably by hybrid modeling.

The ability to blend both types (physics and data-driven) of digital twin into one overarching model negates the limitations of each individual model type. This can lead to greater engineering efficiencies and customer value throughout product lifecycles. As of yet, it seems that the oil and gas industry has not fully taken advantage of the fusion of reduced-order data-driven models with physics-based models. Herein, the need exists for the development of hybrid digital twins.

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E&P Digital Twin in a System of Systems Model

By: Dr. Ed Marotta and Dr. Dale McMullin

INTRODUCTION

The Oil and Gas (O&G) industry strives to produce hydrocarbons from reservoir basins with the highest degree of recovery and the lowest cost relative to the open market rate. Enhanced oil recovery (EOR) from both conventional and unconventional reservoirs can be achieved through multiple options for operators and service providers. Two primary avenues that can drive increased production and, ultimately, oil recovery are fluid injection (water, CO2, steam, etc.) and the installation of artificial lift technologies (ex., ESPs, gas, PCPs). A third avenue currently being explored is the application of data science techniques, such as machine-learning and neural-net algorithms, to glean intelligent insights from data/information gathered from drilled offset wells. These insights are then applied to future analyses to improve future wells. Production wells rarely operate in isolation, and their interactions with other producers and injectors can greatly affect the decline-curve; hence, affecting production over the life of the field. These entwined “systems” of wells drive interactive effects and emergent behaviors that drive a need to incorporate a System of Systems (SoS), or a systems engineering, approach to vastly improve results. Halliburton’s Voice of the Oilfield™ and Well Construction initiatives are examples of “end-to-end” strategies that incorporate this approach.

In addition to conventional well construction, systems engineering also applies to unconventional wells. Relatively speaking, unconventional wells do not typically have offset well interaction and do not remain productive for very long; the average production period for unconventional wells typically lasts less than five years. However, it is important that Asset Lifecycle Management ideals are fully utilized, warranting a systems engineering approach. The exploration, reservoir, well construction, production and petroleum investment lifecycles must each be well-understood and designed in order to ensure maximized returns (e.g. production and ROI). In addition, interdependencies and influences between individual lifecycle stages should also be considered to maximize total production. This “End-to-End Lifecycle” thinking naturally leads to the concepts of Systems Engineering (SE) and Model-Based Systems Engineering (MBSE) to guarantee that performance requirements are met, the right
modeling and simulation standards have existed for decades, including techniques like Finite Element Analysis (FEA) for thermal and stress predictions. However, only until very recently has the ability to accurately model and numerically validate the integrated behavior of very large, complex, aggregated systems of systems (SoS) been possible without the help of extremely expensive and cumbersome super computers. This paradigm shift is made possible due to hardware enhancements (GPUs vs. CPUs), information management, Big Data, intelligent hard/software tools (e.g. Python, Tensorflow, Keras, and Theano), and artificial intelligence (AI) algorithms.

Shifting to MBSE enables technical teams to more readily understand design change impacts, communicate design intent and analyze a system design before it is built. Furthermore, this approach moves the record of authority from documents to digital models that include the use of a digital twin in a data-rich environment; the digital twin simultaneously becomes the simulation model and the execution environment for lifecycle management.

In summary, these advances in hardware and software technologies have enabled the development of the information lifecycle infrastructure, which in turn gives industries the opportunity to explore and take advantage of the exciting possibilities for digital twins to analyze entire systems quickly and efficiently; thus, facilitating our “Digital System of Systems” (DSoS) approach. This article is the first in a series of comprehensive publications that detail how the digital twin, in the context of an SoS framework, can be utilized in the E&P lifecycle. Subsequent articles will highlight the other lifecycles, as shown in Figure 1.

Model-Based Systems Engineering (MBSE) is the formalized application of modeling to support system requirements, design, analysis, verification and validation activities beginning in the conceptual design phase and continuing throughout development and later lifecycle phases (INCOSE SE Vision 2020 INCOSE-TP-2004-004-02, September, 2007). The two concepts are intertwined, since aspects of MBSE are implicit in MBSE and, along with systems engineering, includes behavioral analysis, system architecture, requirement traceability, performance analysis, simulation and validation testing. It formalizes the practice of systems engineering that includes behavioral analysis, system architecture, requirement traceability, performance analysis, simulation and validation testing. It formalizes the practice of systems engineering that includes behavioral analysis, system architecture, requirement traceability, performance analysis, simulation and validation testing.
The notion of SoS™ can be described as an assembly of constituents, which individually may be regarded as systems, and which collectively deliver unique characteristics. These are emergent behaviors that lead to more insightful capabilities and interoperability to exchange information to support a desired SoS mission. Interoperability and the introduction a digital twin enable the seamless exploration of performance scenarios individually among the constituents, or as a cooperative in a virtual environment; hence, a Digital System of Systems Model.

Digital Twin – Historical and Present Day

The ultimate goal of the digital twins for any industry, but especially O&G, is for operators, service and logistic companies to benefit from data-driven solutions incorporating advanced analytics. While the traditional analytical tools that comprise basic intelligence examine historical data, tools for advanced analytics focus on forecasting future events and behaviors, allowing businesses to conduct What-if analyses to predict the effects of potential changes. This enhances the descriptive nature of their business (visualization, dashboards, trending, etc.), along with greater operational prognostication (predictive analytics), that assists the decision-making process once an event has been timely forecasted (prescriptive analytics). Since these alerts will arrive with enough foresight, accurate planning can ensure safe execution. Digital twins with predictive powers will not only provide significant reduction to unplanned downtime, but also reduce planned downtime through a well thought-out logistical planning of manpower, work permits and spare-parts ordering. Multiple examples are obvious during well construction, where variations between wells and fields are the norm. Only through collecting data and applying that data to adaptive analytics will predictions and models be more accurate and valuable.

A formal definition for a digital twin first appeared in the early 2000s. It was originally defined in the context of Product Lifecycle Management. The concept of a digital twin as a virtual representation of what has been manufactured was promoted. The idea consisted of comparing a digital twin to its engineering design to better understand what was produced versus what was designed. This tightened the loop between design specifications and what was actually executed on the manufacturing floor. Subsequently, several more flavors of digital twins emerged (Dr. Grieves, 2014)[2].

- **Digital Twin Prototype (DTP)** — Descriptive information to create an asset (e.g. Bill of Materials and Bill of Processes)
- **Digital Twin Instance (DTI)** — A single specific physical instance of an asset (e.g. list of exact part numbers that went into production of this specific asset, and the exact process steps)
- **Digital Twin Aggregate (DTA)** — An aggregation of multiple DTIs
- **Digital Twin Environment (DTE)** — An integrated, multi-domain physics application space for operating on digital twins for a variety of purposes (ex., Predictive - the digital twin used for predicting future behavior and performance of the physical product)

It is the latter definition of the digital twin that is most relevant to the concept of DSoS. Figure 3 depicts the dynamic and multi-domain nature of digital twins.

Digital twins adapted through high-fidelity analytics with defined systems architecture can provide insight into key system characteristics not evident through traditional analysis alone. Their adaptive nature allows many more system configuration analyses against mission scenarios in near-real-time mode. Again, this approach and capability provides significant benefits and advantages during well construction and production, where variations between wells and fields are the norm. Only through collecting data and applying that data to adaptive analytics will predictions and models be more accurate and valuable.

Present-day thinking of digital twins has now incorporated artificial intelligence, machine learning and advanced artificial neural networks (ANN) to create a dynamic, “living” digital model that updates and changes as its physical asset changes (e.g. fatigue) based on live data. Historical data collected during drilling operations in similar wells and basins are also used to generate data-driven models, maybe in combination with physics models, for every aspect of a well operation to create accurate digital representations of the formation, trajectory, well design and drill-time behavior. This data is then augmented with near- or real-time data from present drilling operations to adapt and teach the digital twin for each particular well and basin. In short, we are using live data to make our models smarter and more useful in a variety of conditions.

A digital twin continuously learns and updates itself from multiple sources to represent their near- or real-time status, working condition or position. This learning system learns from itself and adapts, using sensor data that conveys various aspects of its operating conditions, or from similar fleets of machines, or from larger systems and its environment, with which it may be interacting and/or comprised of.

The customer value-add of any new concept or technology, such as a DSoS comprised of digital twins, must be clearly demonstrated to the customer in terms of financial benefits (lowering Capex and Opex expenses), as an enhancement to engineering and operational efficiency and/ or increasing the ultimate reservoir recovery rate (~15-20% for unconventional and 30-40% for conventional). Several customer value-add aspects of this concept and digital twin technology are:

- **Visibility**: The digital twin allows visibility in asset operations, as well as in the larger interconnected systems.
- **Predictive**: Using various modeling techniques (physics and mathematics-based), the digital twin model can be used to predict the future state. Now, data-driven models are being developed via machine learning and ANN algorithms.
- **“What-if” Analyses**: Through properly designed interfaces, it is easy to interact with and ask the what-if questions to the DSoS model to simulate various conditions that are impractical to create in real life.
- **Connect Disparate Systems**: DSoS, along with the digital twin model, can be used to connect with backend business applications to achieve business outcomes, e.g. supply chain and logistic operations.
E&P Digital Twin in Digital System of Systems

The concept of digitizing asset and system information without documentation is not new, but the addition of incorporating that information in a living virtual representation to extract performance and dynamic predictions throughout its lifecycle is a fairly new concept in O&G.

Figure 4 depicts the potential implementation of the DSoS concept, in conjunction with digital twins, for well construction. The benefits of this idea were clearly detailed in the white paper titled, “Using the Digital Twin in Well Construction.”

In many industries, evidence exists that the application of digital twins for prognostication, reliability-based maintenance and a digitalized factory can have a tremendous beneficial impact if effectively developed and used. The desire to prevent failure at the highest level with the understanding of the failure mode, itself, can provide valuable feedback to design engineering groups. These failures can be a result of interactions or dependencies on other elements comprising the larger asset or subsystem. Examples of SoS’s that are prone to failure during well construction are the drill string (bit, bottomhole assembly, pipe, etc.) and surface equipment (draw works, top drive, mud pump, etc.). All these components must work together in order to drill a well, and as rig operators move to more optimized and automated operations, interactions between components must be both seamless and reliable. The digital twin must enable simplified remote and automated rig operations without failures. If the interactions between the assets and subsystems can be modeled virtually, as an aggregate, it becomes easier to quantify the nature of those interactions, and then to recreate the observed failure. This will provide accurate prescriptive analytic options, by which a preventative or reactive decision can be intelligently arrived at with the highest level of confidence and probability of success.

The most innovative ideas and outcomes are brought about when humans collaborate with each other in order to bring more intelligence, more varied perspectives, better problem solving and out-of-box thinking to complex circumstances. The same can be articulated when the strategic combination of sensors and edge devices/apparatus are integrated with analytics techniques to update digital twins hosted locally or on a cloud-based server.

An example is the monitoring of operating parameters of a fleet of connected automobiles. Based on a Semantics data model, the edge device is intelligent enough to decide when the operating parameters are in the ‘normal’ range and when they are not. Messages can be deciphered as urgent (check-engine light or break-failure notification), which messages are important (low tire pressure) and which messages are routine (the oil viscosity is slowly deteriorating towards an unacceptable range). Also, the best delivery mechanism (cellular network versus Wi-Fi network) can be determined by the model. The collaborative interplay between sensors, edge devices and digital twins allows for more intelligence, insight and decision-making to be brought to bear on valuable data that would otherwise be lost in the dark data black hole. In addition, the DSoS model would allow a shared conceptualization that can be visualized in exactly the same way by an unlimited amount of assets, and seen by individuals who do not need to share the same location via data centers and cloud-based computing capabilities. Figure 5 shows the communication paths between sensors, edge appliances and cloud services from a single well to a full field perspective.

The customer value-add that now exists for sustainable energy wind farms (where individual wind turbines are not just optimized, but entire farms deciphered) can be transformed to the O&G industry (where full production fields are analyzed and optimized). The goal of the DSoS concept is to allow engineers and technicians monitoring a producing O&G field to look at a situation (let’s say, multiple alerts...
levels of economic performance that spans the acquire-to-market spectrum. This paradigm swing is a result of many factors that include local and global demand uncertainty, increased reserve searches, the need for longer asset utilization and a striving for greater operational efficiencies. The combination of digital technologies and market conditions is causing a seismic shift in the industry’s approach to achieve excellence in mining reserves throughout its lifecycle. The digital mine unites the value chain from point-to-point by leveraging digital technologies with the IIoT linked to microservices and/or apps hosted on the cloud or local edge appliances. Data integration, in conjunction with descriptive and predictive analytics, provides the intelligent decision-making capabilities not available in the past. A potential capability is to combine near- or real-time data with machine-learning algorithms joined to a dynamic scheduling to control mineral characteristics with drill and blast, and improved blending, to meet required output. This latter aspect will truly be a market disruptor to this industry.

In the future, core operational processes in the “mine value chain” will be highly automated and comprised of integrated systems, with a wide range of digital capabilities being deployed. Digitized geological data, autonomous vehicles, sensors, wearables for maintenance and operator safety, drones for inspection, remote center operation and digitized engineering and asset information (e.g. “geological digital twin”) will all be the catalyst that will drive the Digital Mine.

Dundee Precious Metals, a Canadian international mining company, combined novel thinking with digital technologies in one of their underground mines. In a proof-of-concept (POC) program, called ‘Taking the Lid Off,’ Dundee demonstrated how numerous data sources, software and location technologies could be combined to create an intelligent Mine Management System. This mining system included such digital features as real-time production supervision, tracking and monitoring. As a result, annual throughput from the mine has nearly quadrupled, unit costs have sunk and a real-time Production Management System has provided a disruptive model for underground mines. However, they failed to mention the use of a “geological digital twin” for predictive capabilities or an integrated SoS approach.

In summary, the mining industry is interested in leveraging revolutionary technologies to take analytics to the next level with performing more real-time and dynamic analyses (e.g. geological digital twin), developing more robust simulations and tying in artificial and machine intelligence. Ultimately, the focus is on using these tools to improve decision-making around the fundamentals of mining, and taking a data-driven approach to determining how to best process the right data to realize the greatest economic value.

The digital oil field is analogous to the digital mine field, where the latter will be connected to a remote operation center (e.g. nerve center) via cloud-based services, asset IIoT and field-operator wearables. In the former, the synergies between reservoir systems, fluid injectors (as the fluid front sweeps through the lithology) and producing well systems become the E&P DSoS model. In the digital mine operations, discovery and appraisal, resource exploitation, product movement and ship-to-market are the interrelated systems that can constitute a DSoS. The common denominator within each model is the digital twin.

In the digital oil field, data captured from each individual well as it interacts with the reservoir can be analyzed and communicated to its existing near-by neighbor (whether producing or injecting) through localized edge appliances at near- or real-time conditions. Operational parameter selection, based on digital twin predictions to optimize each well’s production or optimization of full field production, can be readily realized through cloud capabilities and closed-loop controller edge appliances. As a result, an integrated DSoS approach becomes a natural outcome. Asset-to-the-max or performance-to-the-limit ideas are now achievable through the Voice of the Oilfield concept, where the information exchange highway is being driven by a digital twin. There is no reason why similar enhanced efficiency proclamation for the Digital Mine cannot be translated to all O&G production; especially, for unconventional plays. Figure 6 depicts the full integration and automation that is envisioned with a full field digital twin concept.
CONCLUSION

Computational and sensing hardware, along with software tools, has been enhanced tremendously in the last decade, and the idea of digital twins has grown as an exciting path to utilize the vast amount of information data generated by IIoT devices. Advances in data analytics, coupled with edge and cloud computing, have rendered data storage and its usage much more practical, especially within the O&M industry. These innovations in hardware and software technologies have enabled the development of the “information lifecycle” infrastructure, which in turn gives industries the opportunity to explore and take advantage of the possibilities for digital twins to analyze entire systems quickly and efficiently. When independent systems are integrated, they become interdependent, which is a relationship of mutual dependence and benefit between the systems. System of Systems (SoS) conforms to the accepted definition of a system, in that each consists of parts, relationships and a whole that is greater than the sum of the parts. The idea that digital twins, MBSE principles and SoS can be elevated to the exploration of interactions among multiple systems, as depicted in the Voice of the Oilfield Ecosystem, in a digitized or virtual world constitutes a Digital System of Systems or a Cyber-Physical Systems Model.

ECONOMIC ANALYSIS AND RENDRING

Using the Digital Twin in Well Construction

By: Olivier Germain, Dr. Dale McMullin and Gabriel Tirado

INTRODUCTION

The State of Technology in O&G

In the oil & gas (O&G) industry, the purpose of a well is to increase the capability to produce hydrocarbons at a cost below their market rate. The well can do this by either being the primary conduit for production, or by driving increased production through fluid injection (water, CO2, steam, etc.), or by providing new information that will serve to improve the next wells. The well needs also to be constructed in a safe way, both during the drilling and completions operations, and for later when the well is passed to the production or injection phase. Wells are rarely productive in isolation – and left to their own devices, would likely not remain productive for long. This is why wells are associated with a few lifecycles: the exploration lifecycle, the reservoir lifecycle, the well construction lifecycle, the production and finally the petroleum investment lifecycle. The well construction lifecycle is extremely important, as it determines what the well comprises and the subsequent likelihood of success for other future lifecycles including the reservoir and production.

REFERENCES

INTRODUCING THE DIGITAL TWIN

Digital Twin Concept

While the terminology has changed over time, the basic concept of the digital twin model has remained fairly stable from its inception in 2002 (University of Michigan, formation of a Product Lifecycle Management – PLM center; Dr. Michael Grieves). It is based on the idea that a digital informational construct about a physical system could be created as an entity on its own. This digital information would be a “twin” of the information that was embedded within the physical system itself and be linked with that physical system through the entire lifecycle of the system.

A Call for Change

Those lifecycles are surrounded by one that was less seen and traditionally talked about in the corridors, but that supports and sustains them – the information management lifecycle. In recent years, as the industry has experienced cost constraints and shrinking margins, the need for productivity and efficiency improvements have come to the forefront. Operators want to increase quality and speed at lower costs while constructing wells, which requires real time information to make faster decisions with a higher level of accuracy. In parallel, technology has improved to port the information lifecycle into the digital age, and now that data analytics and cloud technology have rendered data storage and usage feasible to go further than simple “find, retrieve and view data”, and to combine it in a “live” way with models, hypothesis, and different sources, domains, etc. It is now possible to build a rich and complex representation of the current state of the well, predict what could be happening on the field, and then use the difference between the predicted state and the desired state to foster real-time long-ranging data-driven, science-backed, economic-value-based decision making. This is the purpose and the valuable contribution that the concept of a digital twin provides to the O&G industry.

In this paper, we propose an approach to model the wellsite aggregation of surface and downhole equipment as a digital twin, and how this representation may be used in practical applications of digital well design, operations, and hazard prevention in drilling operations. The conclusion of this paper will propose, at a high level, how this basis of modeling and optimization can be further extrapolated to a level of rig-side automation not yet realized in industry.

Applying the Digital Twin to O&G

In reality, the industry has been creating digital twins since equipment and process simulations began, and have been enhancing the mathematics of a static or dynamic interaction, whether fluid on fluid, fluid on rock, rock on metal, or metal on metal. However, these efforts have been spotty, myopic, fragmented, sporadic and ill-used.

The need for a more complete or complex model is dependent on the process being recreated. We see evidence of this application of digital twins in prognostics and reliability-based maintenance and digitalized manufacturing. The desire to predict and prevent failure at the highest level is assigned to the aggregate piece of equipment: the engine, pump, compressor, or gas turbine. Each failure mode itself is more specific. For example, and especially in rotating equipment, failures would be observed in bearings, valves, and other parts that move often and are subject to some kind of physical interaction, and thus an opportunity to fail.

In many cases, the failure itself can be a result of interactions, or dependencies on other elements of the larger piece of equipment. The state of the equipment must often be modeled as a combination of several interacting physical models. This is where we see the logical need to create the concept of a digital twin. If the interaction between the parts can be modeled virtually, it is easier for the model, and also the person or system attempting to understand the nature of the interactions, to understand or recreate the concept of failure on the complex aggregate system. Also, if a mathematical model is not defined or available, it is acceptable and straightforward to associate inputs in a coefficient-driven formulation to...
calculate the outputs of the system, and then model the interaction as a data-driven black box. These models are then further augmented in real-time with additional actual data collected on a given well or operation. By integrating all of the modeling, available data from past wells and live access to real-time data, we are also able to create the richest historical representation of a well or field. In addition, it is also easier to apply software and tools specifically designed to visualize or recreate the physical appearance of the equipment, such as 3D modeling, to be based on the digital twin. We have seen examples of this in live animated versions of drilling rigs, downhole tools, and surrounding reservoirs.

Many of today’s digital twin models are of manufactured systems, which commonly have consistent designs and manufacturing quality controls.

The ultimate goal of the digital twins in the O&G industry is for E&P operators and service companies to benefit from combining data-driven solutions and advanced analytics into one model that will enhance the visualization and predictability of their operations; produce accurate representation of multiple operational environments and challenges to assist the decision making process of the planning phases into accurate and safe execution; provide significant reduction to unplanned downtime; and in overall optimizing the well construction lifecycle management.

Introducing the Digital Twin to Well Construction

The digital twin in the well construction domain of the oil and gas industry is a virtual reproduction of well, rig and downhole equipment using the various plans, designs, and simulations needed to recreate and model operational scenarios. It is a combination of mathematical models, software algorithms, and data models that drive a representation that is as accurate as technically possible. It is also a representation of the actual composition and behavior of a physical asset, equipment or operations, whether in the “what if” or “as is” mode. Because the well is intimately tied with all five lifecycles, those models and data need to also be included in order to represent and drive decisions around the entire system, including the subsurface, the reservoir, the production, and the economics. The well construction model faces a specific challenge not typically found in many other industry models: the uncertainty of its environment, as the composition and properties of the subsurface are mostly interpreted from primary or secondary sources, with an associated component of error. It is especially important as we have to remember that we not only have to ensure that the well does not fail mechanically, the more traditional part of a digital twin, but also that is economically viable – which means contribute to producing more hydrocarbons at a lower cost. This second and key purpose is highly dependent on the knowledge of the subsurface and reservoir, and therefore evaluating, understanding and eventually diminishing those uncertainties associated with the well are themselves a key purpose of the digital twin.

The second challenge associated with an E&P digital twin is the traditional lack of unicity of models – stemming from the times when interpretations and plans were made on paper, but amplified since the days of the digital file and folder system. The E&P has traditionally adopted a very loose approach towards managing validations of latest or approved versions, with most software using at best a simple naming convention of various files to track their ownerships, contents and usage.

The Well Construction Digital Twin Content

E&P operators need the big picture to develop their assets successfully. Once they understand the reservoir’s potential and how to access it effectively, they must operate with the highest efficiency and productively to achieve the performance they have planned. To drill deeper, farther, faster, cycles of quick learning and adjustment continue all during field development. Landmark’s solution to managing the well construction lifecycle is designed to:

- Help maximize reservoir contact and drainage
- Meet and document best practices for continual improvement
- Inform quick decision making for addressing safety, short and long-term integrity, and performance
- Help ensure a positive return on investment, and the selection of the best possible scenario out of all possible combinations
- Quickly react and adapt to unavoidable changes throughout the lifecycle of the well construction

To create a context for the digital twin, the drilling model is composed of four unique, independent elements. These are the subsurface, the wellbore, the rig, and surface equipment. The subsurface is composed of the surrounding geology, reservoir, and near-wellbore formations. In order to derive the objective functions to execute during well construction, we identify four integrated primary elements to be modeled.

- Wellbore trajectory
- Drilling physics
- Pressure control (mud properties)
- Reservoir composition and integrity (near Wellbore)

Responding to a Call for Change

Within the digital twin, these elements are modeled to state and action are captured and predicted as one combination of parallel, and in some ways competing, behaviors. Each element is susceptible to changes in all inputs simultaneously, increasing complexity.

The wellbore is filled with downhole equipment in interaction with the subsurface. This depends on the stage of development for the well. During drilling, the well will be in its construction phase, with a drilling list, casing, and BHA (bottom hole assembly) components. During the completion stage, the wellbore may have casing, and may also contain fracking tools, packers, screens, and other completion tools. Finally in production, the wellbore will receive tools for artificial lift, injection, and other production processes. The fluid that will be used to maintain the pressure of the walls of the wellbore will also differ during the various phases of the well construction. During the operation phase, the properties of the BHA will affect overall well construction behavior. Critical equations used to continuously test drilling behavior include torque and drag, vibration, and others.

The rig consists of any equipment directly associated with drilling, but not downhole. This includes the hoist, mud pump, top drive, rotary table, or Kelly combination, and draw-works. In order to complete this model, and in some cases connect interacting components, the rig also includes any rig-side plumbing or electrical connectivity.

Surface equipment is largely self-explanatory, and for this paper includes elements not on the rigfloor or directly associated with the drilling process. These elements are more supportive, but may still have important dependencies when calculating or predicting on the aggregate system. These elements include the power plants, pits, tanks, and any other non-rig piping or electronics.

As soon as well construction operations start, a four-stage cycle begins. First, the
A prototype that was built during the plan and design phases is updated with all values at the current time step. The digital twin needs to be set to the representation of the current state of the well. The next stage is to look ahead in time, and based on historical data and current equations for calculating direction, fluid properties, and wellbore conditions, the state of the digital twin is projected forward. This predicted value is then compared to the desired state of the model. Again, all of the elements are updated simultaneously. If the comparison of future predicted state to desired state is significantly different, a number of optional scenarios must be run in order to determine a corrective course of action. This can be accomplished by utilizing an optimizing algorithm across a number of possible solutions. Once a course of action is determined, the last step is to create a series of advisory steps or settings for rigfloor controls to make the changes a reality. All information related to monitoring, prediction, and control is collected for future reference.

Since this model includes the subsurface and surface elements as described, the operator acquires significant information about the well and its environment. It is vital for further studies and understanding of the behavior of the well and the field that this information be kept as part of the digital twin, in order to make future models better. This information is of two types:

a) Information acquired with the specific aim of understanding the subsurface – those can be wireline or MWD (Measurement While Drilling) logs, Surface Data Logging results, cutting sample analysis, etc.

b) Information derived from the operations themselves: daily operation reports, or real time equipment performance logs.

The first type will help refine and correct the subsurface, reservoir and wellbore models, while the second type is used to understand how to improve operational efficiencies. However, as data analytics techniques improve, it is interesting to note that the second type can also be used to supplement or replace the first by being the input that an AI system can use to generate synthetic logs.

By integrating all of the modeling software, available data from past wells and live access to real-time data, we are able to create the richest unified representation of a well construction preparation or execution. The unified set of models are a combination of plans and actuals, including their respective interpretation and execution uncertainty – thus helping to achieve the highest possible level of fidelity based on the latest information. Models are always updated and plans are kept live; consistency is achieved due to their unified representation (see Figure 3).

One of the key elements of the Landmark digital twin is to ensure that only the version of the models that is the most current (not necessarily the latest) in terms of validity and approval is being used to process decisions. Due to its federation and storage capability, the Halliburton’s DecisionSpace® platform integrates all the various aspects of the business process linked to that approval and “publishing”. It is particularly important during operations, where delays are costly and decisions need to happen fast but be correct, that this can be done efficiently. At this time, through the drilling process and the acquisition of logs described earlier, interpretations are constantly revised, the uncertainties on the subsurface and reservoir models are reduced, and better forecasting can be made, leading to safer, and lower cost per barrel, typically due to a combination of improvement of the reservoir contact while lowering the cost of completions.

The well construction digital process starts with Halliburton’s DecisionSpace Well Planning and well construction software that create the basis for intended design and modeled physical constraints, providing a single platform that integrates applications and databases across the organization from seismic to production, to close connectivity gaps between disciplines and departments so that workflows can be integrated for collaboration throughout the field development process.

This data is first augmented with historical data collected during live drilling in other similar types of wells and similar basins that are used to create data driven models for every aspect of the well to create accurate digital representations of the formation, trajectory, well design and drill-time behavior to name a few. The well digital twin pulls all inputs, which already reside in Halliburton’s EDT™ software (Engineer’s Desktop™), together. This virtual
version of the well then enables the Digital Well Program™. The Digital Well Program is used for optimization of drilling and well performance by aligning operators and service providers around the well construction process and lifecycle management.

The well design is converted via the Digital Well Program into a set of machine readable detailed instructions for surface and downhole equipment. The Digital Well Program provides a systematic methodology that helps to reduce preparation costs and increase automation and integration, through orchestrated workflows with seamless connectivity with operations. Once initial planning and design is complete, the Digital Well Program automatically checks for potential inconsistencies, then accelerates the approval process of the program and makes it available for the right people to consume. The well digital twin is up to date, now drilling begins and the well digital twin is able to automatically send electronic instructions like weight on bit to smart rigs. As companies evaluate strategies to reduce costs, optimize well operations and assets production, they will need a greater understanding of the financial, technical and operational segments to be successful in today’s environment; the well construction digital twin can help improve the overall well integrity index and well construction processes, supporting the development of efficient and agile well construction workflows, and facilitating decision making towards the most rewarding exploration, drilling, completion and production alternatives.

Opportunities for Operators & Call to Action

Today, most operators are using part or all of the Landmark traditional solution, the EDT suite, to manage their well construction lifecycle. Few if any however use it to the full extent of its power, and enable a Digital Twin to become part of their daily activities. In particular, data repositories (EDM™ databases) are multiplied, interactions are not tracked and changes are not monitored (SAM™ or Simultaneous Activity Monitoring is disabled or not installed), plans are not systematically completed and stored (engineering and operations data kept separate), AFE are not generated from that plan (WellCost not present), so that deviations cannot be noted and later analyzed, real-time results are not aggregated or properly transcribed (e.g. deviation survey data imported from simplified Excel spreadsheet and not from a QAC QC Compass process), NPT events are not tagged and annotated so that a Root Cause Analysis can be performed and trends can be discovered, parts and suppliers catalogs are not maintained leading to multiplications of records, and so on. At the end, the suboptimal set up means that a lot of work needs to be done time and time again, data is exported and imported, or retyped, errors and omissions abound, and frustration is high. Worse, while the system performs its function at the sub-process level (e.g. validating that a particular piece of casing will withstand forces and actions in a set activity), no validation is run to ensure that decisions made in one part of the process do not negatively affect another part (e.g. change in mud properties improve cutting transport and T&D, but change thermal properties and affect casing integrity).

This is the reason why Landmark is now enabling an iENERGY cloud-based solution that will take a lot of guesswork and configuration complexity out of the equation, leaving only critical and company specific policies to set up, such as the RACI chart of decision-making. By enabling the Digital Well Program described above, operators will now have a system where when any changes are made, the whole is kept consistent, always up to date, even where even third parties are working from the same set of assumptions. As importantly, by creating this digital twin, both at the prototype and at the time of execution, in a consistent way, with a single shared representation of the latest set of information, operators will be able to retain lessons learned, and create a naturally occurring continuous improvement system, where tacit knowledge becomes an explicit insight, easily found, reproduced and reused. Broadening the solution beyond the boundaries of the EDT suite will also enable operators to not only become more efficient and safer (through simplified workflows, communication transparency, etc.) but also help them become more effective by placing wells where more hydrocarbons can be found and extracted at a lower cost. It will also give them the fundamental tools to use or develop proprietary analytics algorithms to search and apply ways of better selecting suppliers, tools, parameters, so as to drill and complete holistically better wells.

CONCLUSION

As companies evaluate strategies to reduce costs, optimize well operations and assets production, they will need a greater understanding of the financial, technical and operational segments to be successful in today’s environment; the well construction digital twin can help improve the overall well integrity index and well construction processes, supporting the development of efficient and agile well construction workflows, and facilitating decision making towards the most rewarding exploration, drilling, completion and production alternatives.
Digital Twin Implementation for Integrated Production & Reservoir Management

By: Suryansh Purwar, Zainub Noor, Dr. Egidio (Ed) Marotta, Raed Charrouf, Dr. Cesar Enrique Bravo, Dr. Shaoyong Yu and Dr. Dale McMullin

INTRODUCTION
The trying times endured by the oil and gas industry in recent years have forced companies to re-evaluate their operational costs and production optimization methods. This has driven the acceleration of efforts to leverage digital technologies and commence digital transformation. Unlike other project initiatives, digitalization is a journey, in and of itself, that requires a systematic approach and fundamental changes to the traditional work environment.

Thanks to improved technology, several tools are now at the disposal of exploration and production (E&P) companies looking to embark on a digital journey of their own. There are many components to the digitalization process, including big data analytics, automation, machine learning, artificial intelligence and cloud technologies. However, one concept, in particular, that has a huge potential to provide a lot of upside to engineering operations is the digital twin.

The notion of a digital twin originated in 2002, when the term was first coined by Dr. Michael Grieves. In layman terms, a digital twin is a virtual model/representation of a process, product or service. This pairing of the virtual and physical worlds allows analysis of data and monitoring of systems to head off problems before they occur. This can prevent downtime, help develop new commercial opportunities and assist with planning for the future via rapid and inexpensive simulations.

The International Data Corporation (IDC) predicts this concept will save companies at least 30 percent in process improvements. It is, therefore, not surprising that the digital twin was named one of Gartner’s Top 10 Strategic Technology Trends for 2017.

Leveraging a Digital Twin for Integrated Reservoir and Production Management
Reservoir and production systems have always been closely tied. The reservoir performance,
As determined by various simulations, has traditionally been used as an input to model the well's ultimate recovery efficiency under various development scenarios. Comparisons of the rate of return from the different production approaches and recovery methods can then be made. During ongoing operations, production history is used for updating the reservoir simulation models through history matching to establish confidence in the validity of the model. Both production and reservoir models are used together to assess the scenarios for future development of the reservoir.

Most of the current planning processes involve numerical models that represent the real space digital twin instance of a very specific operational process, infrequently invoked on an as-needed basis. Even without leveraging the full potential of the digital twin solution, many operators struggle to maintain and use these offline instances. It is a clear indicator of how far-off the oil and gas industry is when compared to other industries regarding digitalization and realizing the upside of these new approaches.

As oil and gas systems methodologies and technology have improved and become more integrated, a corresponding increase in automation complexity has occurred. Equally important, performance and health-state information generated during daily operations has become a key asset for these integrated systems to manage. This ever-increasing tide of data has led to new requirements on its governance and flow in order to maintain visibility and control. Such requirements were born of a desire to move away from collecting data in silos and to capture metrics using all available data to generate meaningful insights. Interoperability of data and cross-domain workflows has gone from a nice-to-have to a must-have as organizations continue their focus on efficiency and intelligent decision-making.

The introduction of a digital twin for integrated reservoir and production management is, therefore, an ideal solution for the management of an integrated oil and gas production and reservoir system with its greater complexities. This allows the collaborative exchange of information, and it supports more accurate, efficient and intelligent decision-making; therefore, addressing today’s most pressing challenges.

The digital twin is the “information vehicle” that enables systems to seamlessly exchange vital information among the integrated production and reservoir subsystems to accomplish the main mission—to achieve the highest possible recovery and transportation at the least cost and the highest engineering efficiency from pore-to-facility. Hence, it helps solve the problem of information-flow complexity. Also, the digital twin becomes the vehicle that provides the health-state status for integrated systems, from which preventive and remedial actions can be taken. As is often the case with optimization opportunities, the more vertically integrated the assets, the easier it will be to capture all the benefits resulting from a system-wide digital twin approach.

According to Dr. Grieves, there are various implementations of a digital twin:

» Digital Twin Instance (DTI): Replicates the asset and current sensor measurements “as is”

» Digital Twin Aggregate (DTA): An aggregation of multiple instances

» Digital Twin Prototype (DTP): A multi-dimensional representation of a producing asset, not a specific replica

This paper outlines an applicable framework of a digital twin for reservoir and production lifecycles, as shown in Figure 1. The development of a digital twin for integrated reservoir and production management by Landmark (a business line of Halliburton) will leverage the enterprise capabilities of the DecisionSpace® platform and its industry-leading production and reservoir technology. This provides a unique, first of its kind solution by implementing an aggregate twin to very challenging problems, namely, how to handle the complexity of integrated systems, and systems versus asset optimization.

**DIGITAL TWIN FOR PRODUCTION**

A digital twin contains information about a piece of equipment or asset, including its physical description, instrumentation, data and history. Digital twins offer strong potential for enhanced customer value by achieving better insights on surveillance, monitoring and optimization; and, in turn, it drives more intelligent decisions both economically and technically. While there are risks like over-engineering a simple problem, technology overkill and concerns about cost, security, privacy and integration, they can be mitigated by judicious definition of applicable use cases. It is imperative that we use digital twin models to enable disruptive IoT solutions that deliver meaningful business outcomes. For a production digital twin, these outcomes have been identified as:

» Condition and Performance Monitoring (CPM)

» Well Design and Performance Optimization

» Surface Network Operational Optimization

» Integrated Asset Model

Each of these areas will be detailed with specific use cases. However, to achieve the right outcomes, the following principles need to be kept in mind:

Digital maturity: The impact of digitalization is influenced by an enterprise’s readiness to adopt IoT initiatives that leverage digital twins. Simple but impactful solutions: Do not over-engineer a problem if the core issue can be resolved with basic, descriptive analytics.

Assess which business challenges can be resolved with basic, descriptive analytics. Each of these areas will be detailed with specific use cases. However, to achieve the right outcomes, the following principles need to be kept in mind:

Digital maturity: The impact of digitalization is influenced by an enterprise’s readiness to adopt IoT initiatives that leverage digital twins. Simple but impactful solutions: Do not over-engineer a problem if the core issue can be resolved with basic, descriptive analytics.

Assess which business challenges can be significantly mitigated by using digital twin initiatives.

Regular check points: Digital twin solutions cannot develop in isolation and require a good level of engagement on the part of the asset teams. An iterative Design Thinking approach is the most applicable here.
In the past, traditional monitoring solutions filled up large historical and real-time data repositories, and 24-hour manned monitoring centers were used to react to process failures. While these centers no doubt improve efficiency by a few notches, they are not easily scalable or flexible enough to accommodate changing needs. They are also susceptible to human error (experience, tiredness, motivation, etc.) and challenge process efficiency.

To address this challenge, digital twin solutions need to sense, diagnose and predict the physical twin behavior. This can be accomplished by leveraging edge and cloud computing. The combination of real-time and big data analytics models enable a digital twin to be created, reflecting the actual conditions. This, in turn, provides the means to predict various scenarios under given conditions, enable several workflows and provide meaningful operational insights.

When applied effectively, connected infrastructure could revolutionize oil and gas operations. Typical examples are regular reporting of asset well-being and diagnostics when an asset may be malfunctioning. As reserve replacement becomes more challenging, new projects are moving into deeper water and remote areas like the Arctic. The digital twin system combines accurate, real-time information on remote assets via cloud technology. This could reduce cost significantly, along with inherent HSE risks. It would also allow oil and gas operations to move from a reactive monitoring approach to a more predictive management approach, empowering field personnel to make rapid decisions. This would allow office-based engineering and management teams to focus on short- and long-term strategic decisions based on near real-time data.

Well Design and Performance Optimization

A well model is one of the most prevalent examples of a digital twin aggregate in the E&P industry. Engineers have traditionally used well models to predict tubing and pipeline hydraulics and temperatures. Every production engineer routinely uses a well model to tweak various parameters to optimize the operation of their current well design and assess the effects of proposed future changes. The various components that constitute a well model—fluid characterization, reservoir inflow, flowline and tubing, multiphase flow, artificial lift, etc.—can easily be considered an instance. There are several Halliburton applications that address various engineering areas. Each of these different instances, or components, that work in conjunction with the well model is an aggregate.

The current approach of an offline aggregate representation run on-demand, while beneficial, has its limitations when used for design and optimization in real time. Firstly, maintaining a validated aggregate in sync with multiple data sources is a challenge for most companies. Secondly, each run of this well model takes time, which, even if it is a few seconds, compounds itself several times over when running an optimization scenario where several thousand iterations need to be considered.

What is required is a well model that can allow a simple representation of well productivity based on physics calculations or data-driven models. This can be used to help calculate future production based on past trends. Offline aggregate models should only be used to evaluate specific engineering scenarios. A well digital twin prototype, on the other hand, can facilitate the evaluation of multiple scenarios. Engineers can choose completion configurations, model artificial lift methods while evaluating the well performance and design, and use a data-driven modeling approach to realize several thousand scenarios to optimize well configuration. Additionally, it can enable the real-time update of data from existing source systems, data that will be validated and checked not just for correctness, but for engineering feasibility as well. New completion components, such as flow control, pumps, etc., can also be conceptualized, designed and tested in the digital twin prototype before the well is drilled, helping to manage real-world uncertainties.

Once this prototype has been benchmarked and validated, it can be used to accurately predict well performance based on current measurements. When the prototype is available with updated, reliable real-time data, it is more likely to be used. It also affords the engineer the luxury of simulating multiple scenarios, providing a range of solutions. This helps to further reduce uncertainty and improve the likelihood of a desirable outcome by giving engineers the tools and insights necessary to prepare for any planned or unforeseen event.

Surface Network Operational Optimization

One of the main objectives of surface network modeling tools is to help identify system bottlenecks, allocate production and gain greater control of operating data. Optimization tools help provide enhanced solutions, starting at the wellhead all the way to the processing facility. Fluid property modeling, combined with process simulation and optimization, provides more accurate economic and technical solutions. These solutions have the flexibility for building complex network models; hence, their importance to oil and gas production.
System network behavior is modeled with commercial simulation software. This enables the modeling of single and multiphase fluids through the use of mechanistic models, and the inclusion of heat transfer effects and comprehensive equation-of-state PVT models. Production surface network systems analysis allows well performance (multi-lateral or single) to be predicted regardless of orientation, fluid phase, compositional variations or whether it is natural flowing or assisted. This holistic overview of the entire network system allows certain behavioral characteristics to be quantified. This includes how different branches of the delivery chain affect one another and how different field operations interact with one another (e.g. field constraints, pipeline bottlenecks, well potential). It also helps define the design and operating criteria for a given field.

Ultimately, surface network modeling allows for the digitalization of surface assets for quick and accurate prediction of their performance and scenario planning without having to physically build and test the network. In essence, this virtual network is a digital twin of the physical system, all the way to the exit point (sales point). The whole process, as described above, can be vastly simplified using a digital twin system. IoT sensors that communicate with each other are able to interpret all vital information at the local point and connect with other reduced-order IAMs to enable the modeling of any given operating scenario.

The benefits of IAM include time and cost savings by accelerating the decision-making process by ensuring cost-effective project planning of the subsurface development and surface infrastructure. It can also incorporate a variety of uncertainties associated with the execution and operation processes over the entire lifecycle of the field. This leads to greater reduction in non-productive time (NPT), invisible lost time (ILT) and maintenance expense. A major Middle East operator, for example, was facing poor pump pressure and production deferment in several mature oil wells. Instead of installing new electrical submersible pumps (ESPs), the operator used real-time analytics to make proactive adjustments to ESP operating conditions to better suit the changing reservoir conditions encountered for each well. This reservoir-level intelligence improved recovery by more than seven percent, over and above the benefits of reducing non-productive time.

**DIGITAL TWIN FOR RESERVOIR**

**Collaboration Between Production Operations & Field Development**

Reservoir or asset management is a vital process for field optimization during the entire field lifecycle. This helps ensure the short-term production targets and longer-term objectives are met to increase sweep efficiency and maximize the ultimate recovery. Globally, most fields are in a mature phase, requiring infill drilling or advanced EOR (enhanced oil recovery) techniques to produce from depleted reservoirs. There has also been an increased implementation of smart completions and multilateral wells to improve recovery and prolong the life of the reservoirs. All these technologies and techniques pose a high cost to the operators. Therefore, modeling these scenarios accurately before implementation is crucial to avoid drilling into non-productive zones and/or reduced production due to inappropriate well designs. Collectively, this can help reduce the uncertainties associated with the field development plan.

The vision is to develop a reservoir-production digital twin, to connect the physical reservoir to the digital models, incorporating the economic implications of the chosen production and development schemes. The proposed solution would be a combination of several interacting models that represent the different parts of the production process, including subsurface, wellbore and surface facilities. Each component would be accurately modeled by specialized software for that specific element of the integrated model. This will allow analysis of the asset, production monitoring and asset development using a combined virtual model. The integrated reservoir digital twin will enable reservoir management and production teams to work together on a single integrated model. Reservoir simulation will be the point at which reservoir management and production models come together and will help ensure that the integrity of the models is maintained. This can be achieved by using the same asset model for operations and field development.
Assessment and re-development of existing assets require careful planning and analysis to identify recoverable reserves previously missed or deemed inaccessible. Best practices include:

- Advanced scenario planning: Drive up return on investment
- Cross-discipline collaboration: Help meet production goals, minimize risks and accelerate time-to-value
- Optimization: Based on predefined asset development strategies

**Elements of the Overall Solution**

The integrated digital twin will provide a comprehensive solution, allowing all asset teams to interact with a common and unified vision of the asset. All development plans will be able to leverage the current status of the asset, and production operations will benefit from real-time data coming from the field.

Key pieces of the solution include:

- Reservoir simulation: Assess, validate and plan reservoir development
- Wellbore simulation: Design well plans and completions
- Analysis of uncertainty and optimization: Identify key parameters that affect outcomes and provide optimal solutions
- Well production analysis and design: Combine lifting methods and well types
- Gathering facilities and network modeling: Propose optimal surface facility designs and management
- Reservoir fluid properties: Accurately model fluid properties and, therefore, flow of fluid in the reservoir
- Economics and finance: Understand the value-add propositions leading to intelligent business decisions

**Optimization Across the Entire Reservoir Lifecycle**

To model the complete behavior of the asset, engineers need to model flow within the reservoir, through wells and surface facilities, in an integrated fashion. The reservoir, production and completion engineers currently work in silos, focusing only on their elements and passing data and models from one team to another. The impact of change is often a one-way relationship, with optimization occurring at each step based on the specific objectives, but not considering the overall optimization of the entire asset operations.

The operational asset model will allow monitoring of the field operations and changes in the reservoir conditions. This will enable reservoir, production and completion engineers to work together on integrated models, to understand how changes in one part of the model impact the whole integrated system. By working together, the overall recovery from the reservoir can be optimized through more effective development strategies, to meet the short- and long-term goals of the company.

Now, more than ever, in today’s complex drilling environments, engineers must consider the behavior of the total asset when deciding on a development plan. Advanced science-based simulation software provides users the ability to couple surface and subsurface flow models, ensuring an accurate solution. These tools also allow utilization of historical data and enable asset teams to design optimal field development strategies in the short and long term. Surface facilities can significantly impact and constrain production, especially when there is a complex system of networks or where the platform may be miles away from producing wells (e.g., deep water assets). This becomes even more critical in multi-reservoir assets, where individual reservoirs are connected through a shared network, with each unit impacting the production of others. An integrated, multi-reservoir model is needed to accurately determine the interactions of these reservoirs and improve production, ultimate recovery and life of the asset.

A reservoir digital twin would provide optimal solutions for conventional and unconventional reservoirs by providing comprehensive solutions that maintain the integrity of geological features. They would improve accuracy, and efficiency to help operators maximize the rate of investment for their assets.

**WORKFLOW EXAMPLES**

By using the reservoir-production digital twin, multiple workflows (including integration analysis) will be possible utilizing part of or the entire technology suite. Some of the key potential workflows include:

- Well Production Allocation (WPA): Production allocation for single wells to obtain the optimum production of oil or gas
- Field Allocation Optimization (FAO): For an entire oil or gas field, by calculating each well’s production capability at different time steps to obtain optimum field production
- Field Development Optimization (FDO): Optimize plans on a well and field basis by running tightly coupled short- and long-term production scenarios (well model, reservoir model, completions and surface network) through the optimization engine
- Completion Optimization (CO): Assessment of various completion techniques on production for a single well or group of wells, including multilateral wells (for example, inflow control devices, inflow valves, sand control, etc.)
- Integrated Asset Management (IAM): Identification of bottlenecks in surface facilities that may limit production for a single or multiple-reservoir field, and impacts on production of each well
- Enhanced Oil Recovery (EOR): Production optimization from each well and maximizing the ultimate recovery based on enhanced recovery mechanisms
- Holistic Field Development (HFD): Development of technically and economically feasible field development scenarios from early stages to a late mature field stage up to abandonment, with key consideration of development economics [cost of development per well, net present value (NPV) and rate of return (ROR) for the entire portfolio]. Economics needs to be one of the main drivers for technical decisions.
The key objective is to provide a single asset representation that can be optimized in collaboration with the reservoir, production, and completion engineers, as well as the field operations team. This would enable business and technical problems to be addressed and objectives to be met.

INTEGRATED RESERVOIR-PRODUCTION DIGITAL TWIN: A CASE STUDY

Water-flooding optimization is a great example of the implementation of an integrated reservoir-production digital twin. In this instance, a Smart Water Optimization (SWFO) workflow for a National Oil Company (NOC) in the Middle East is presented as an illustration of a digital twin (1). The SWFO workflow enables optimization of water sweep and utilization efficiency through smart coupling of wells and subsurface models, or digital twins, with reactive and semi-proactive optimization strategies.

This workflow comprises two sub-workflows that are executed in two different timeframes. The first sub-workflow is focused on the short-term reactive optimization of settings for surface chokes and water injection rates. The second sub-workflow targets mid- to long-term proactive optimization, which supports field development planning for workover actions and new well types and locations. The main objective of SWFO is to develop an automated workflow to monitor, diagnose and optimize waterflooding process systems. This would use an intelligent, real-time control process that can provide proactive recommendations for water injection and production systems. Specifically, the objective is to maximize oil recovery and reduce water production by achieving a better balance of water injection across the field during a 24-month period.

The smart workflow comprises these major steps, as shown in Figure 2:

- Capture and consolidate the production and injection data every month
- Run the reservoir model and compare results with history data
- Refine reservoir parameters
- Automatically update the reservoir simulation model
- Run the reservoir model and compare results with history data
- Refine reservoir parameters
- Calculate the waterflooding KPIs
- Provide actions if indications are above or below target values.

This user interface presents a digital twin of the field that enables the user to evaluate different scenarios and help them decide the most appropriate course of action to optimize the field operation.

This integrated digital twin allows optimization scenarios to be run for water injection in the reservoir, taking into account changes in the production system. The workflow calculates the optimal configuration of injection/production wells to optimize the sweep efficiency and maximize the ultimate recovery.

CHALLENGES

Due to the complexity of the production and reservoir systems and the difficulty in modeling them individually or collectively, deterministic models are used to make performance predictions. Determining the optimal operational parameters with the incorporation of constraints is the next logical step. Inherently, the uncertain nature of the model predictions, input processes and material properties can lead to inaccurate outcomes. Unfortunately, uncertainties are frequently ignored in reservoir and production optimization. This is due to many engineers and scientists using nominal values to solve these deterministic problems, with a disregard for varying prediction accuracy. Such is the case in most realistic production applications. Hence, the uncertainty associated with predictions from digital twin analysis will need to be quantified and taken into account in decision making.

A critical aspect of deploying the digital twin concept successfully, for production, is human involvement. Connected infrastructure will report accurate information in real time, but skilled humans still need to interpret and analyze the information, to turn it into actionable insight to inform better decision making. Digital twin applications also need to be designed with health, safety, and the environment considerations, this ensures human-in-the-loop involvement when needed and, thus, the CPM (Condition and Performance Monitoring) systems are, themselves, monitored.

Rather than taking the place of human beings, the best digital twin applications will enhance their abilities to make more accurate decisions.
therefore, initiating cost reductions, enhancing capability and, most importantly, reducing uncertainty. This will help the oil and gas industry to maximize the financial potential of their operations in an increasingly uncertain environment.

CONCLUSION

The benefits of a digital twin will only be realized as part of a comprehensive digitalization strategy. The framework of this strategy is a critical question for operators to address with regards to legacy fields and new developments. A high-potential field may warrant placement of more sophisticated sensor sets to generate further insights, not prior attainable for operational conditions, at both the well’s topside operations, and additionally, its subsurface. A field with moderate potential could benefit from the inclusion of sensors for pumps, valves and other assets to create CPM maintenance schedule. A field with low potential may only require standard automation and monitoring systems to keep the well streaming at its optimal level.

Once this stratified approach to asset sensorization has begun to bear fruit, a digital leap towards advanced analytics (condition monitoring KPIs, performance metrics, etc.) could start creating new value on the optimization and maintenance fronts. Legacy field issues, such as gas interference, equipment choking, fluid degradation due to over-pumping and inefficient recovery due to under-pumping, could be addressed in a secure environment. However, according to Gartner, by 2022, roughly 70 percent of data analysis (e.g., analytics) will be done on the edge. Safety-critical operations and processes cannot afford the delay to connect to the cloud; hence, edge appliances will be crucial in performing on-site analyses. This will be a challenge for the industry, and operators will need to decide if they want to move to the cloud or leverage edge technology to analyze the data at the edge of the production network. Although the benefits vary from field to field, optimizing production in a 100-well project can generate annualized cash flows as high as USD 20 million (approximately USD 20 billion at an industry level), leaving aside the cost avoidance for equipment failure and repair.

The digital twin has a huge potential to improve efficiencies and cut costs across all lifecycles in the oil and gas industry. Progress is being made with the development of a digital twin for well construction, and efforts are underway to do the same for exploration and reservoir management. As operators evaluate those strategies for reducing costs, and optimizing operation facilities and production assets, they will need an understanding of the financial, technical and operational flow of information across systems to be successful. In so doing, integrated production systems and reservoir digital twins will help improve the overall recovery index for a particular field. This is the value proposition to the E&P industry.

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Flow Assurance

Digital Twin for Corrosion

Data Driven Modeling –
Digital Twin for Corrosion
Flow Assurance

By: Dr. Matthew Franchek, Dr. Egidio (Ed) Marotta, Dr. Dale McMullin,
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INTRODUCTION

The prediction of corrosion rate and its migration is of paramount importance to the oil and gas industry. In fact, the total annual cost of corrosion to the industry is estimated to be $1.372 billion (1). This cost includes $589 million attributed to surface pipelines and facilities, $463 million in downtime tubing expenses, and another $320 million in capital expenditures related to corrosion. Effective management of corrosion will contribute towards achieving the following benefits; per NACE International (1), towards achieving the following benefits; per NACE International (1),

- Effective management of corrosion will contribute towards a reduction in deferred costs of $589 million in capital expenditures related to corrosion, $320 million in other expenses, and another $463 million in downtime tubing expenses. NACE International (1),

- Reduction in unplanned maintenance
- Reduction in leaks
- Increased plant availability
- Reduction in unplanned maintenance
- Reduction in deferment costs

One of the more complex problems in predicting corrosion rates caused by carbon dioxide, is the effect of multiphase flow since many of the pipelines and flow lines carrying oil and gas are operating under two or three-phase flow conditions. Many different flow patterns can be found, but most common are: stratified, slug and annular flow. In the liquid phase, water and oil can flow separated or mixed, with either phase being continuous with the other flowing as a dispersed phase. Different flow patterns lead to a variety of steel surface wetting mechanisms which greatly affect corrosion. In the absence of protective scales, multiphase flow can lead to very high fluctuating mass transfer rates (particularly in slug flow) which, in turn, can greatly affect the corrosion rate.

The theoretical fundamentals of the carbon dioxide corrosion process can be classified into three major categories: 1) mechanistic, 2) empirical and 3) semi-empirical models. Each modeling type will be detailed in the upcoming sections. However, the data-driven modeling approach demonstrates how the development of a digital twin might encompass the latter two categories. This is purposely done to minimize the computational time, memory, and central processing units (CPUs) requirements needed to predict a corrosion rate when ingesting real or near real-time data from sensors.

A very general overview of the fundamentals underlying the carbon dioxide corrosion process is presented. The various techniques adopted to mathematically describe the process is included, and several approaches that attempt to simplify this complex phenomenon are reviewed with the emphasis placed on a new data-driven mathematical model, which enhances the performance of the DeWaard–Lotz-Dugstad CO2 corrosion model (2). The basis for this enhancement lies on a data recalibration approach to building a “Linear Parameter Varying” (LPV) model. The objective of this article is to showcase how open literature corrosion data can be translated into knowledge using data-driven modeling techniques, which can lead to a digital twin for descriptive, predictive, diagnostic, and prescriptive purposes for pipeline and flowline corrosion. A novel linear parameter varying approach is introduced that addresses limitations to a widely used corrosion rate model in the oil and gas industry, which includes the effects of PH and flow velocities in its prediction. This helps enable the basis for a digital twin corrosion rate predictor, which can incorporate real or near real-time sensor data from flowlines.

Steady State Multiphase Flow Models for Liquid-gas Mixtures

Multiphase flow in pipelines in the oil and gas industry presents numerous engineering challenges for system/component design, operation and maintenance. Corrosion of pipeline, which is a major contributing factor to pipeline damage and system unavailability, is directly affected by the oil/water/gas flow characteristics. For example, different oil-water flow patterns lead to a variety of pipeline surface wetting mechanisms that significantly affect the corrosion rate. Also, in the case of gas presence, different gas flow rate conditions may result in different liquid slug frequencies that directly affect the pipeline corrosion rate. Therefore, it is important to predict and identify the flow characteristics in multiphase flow conditions, which are critical for corrosion analysis.

The oil-water-gas three-phase can be considered as a combination of oil-water and liquid-gas two-phase flows. If the oil and water are well mixed the three-phase flow is equivalent to a liquid-gas two-phase flow. Generally, six different liquid-gas flow patterns can be identified, namely:

- Bubble flow: in this regime, fluid moves as small and dispersed bubbles through a continuous fluid.
- Dispersed bubbles flow: in this pattern, the bubbles are dispersed into smaller and more widely separated bubbles due to velocity increase of the continuous fluid.
- Stratified flow: this regime occurs when the fluids are separated into different layers, with lighter fluids flowing above heavier fluids.
- Annular-mist flow: in this flow pattern, the lighter fluid flows in the center of the pipe with small droplets of the heavier fluid, which is contained in a thin film on the pipe wall.
- Intermittent flow: this regime is composed of both plug and slug flow

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regimes. In plug flow, elongated gas bubbles separate liquid plugs. In slug flow, the elongated bubbles increase in size and separate by liquid slugs.

- Froth flow: this flow pattern is a transition between dispersed bubble flow and annular-mist flow and also between slug flow and annular-mist flow. Greater detail and illustration of these flow patterns can be found in Bratland (3).

The liquid-gas flow is the most common studied two-phase flow. Different approaches have been adopted to predict the flow pattern in multiphase flow conditions. The simplest approach for two-phase flow modeling is the homogeneous flow model where the relative motion between the two phases is neglected and the flow behaves as single phase with properties defined as weighted averages of the individual phases (10-13). A second approach for two-phase flow modeling is separated flow modeling where the phases are travelling at different velocities and allowed to slip relative to each other (6). In this approach, correlations are developed to determine the shear stress at the two-phase contact with the pipe wall (6, 7). A third class of models that has been widely used is the drift flux models. Originally derived by Zuber and Findlay (8), this model uses a distribution parameter and an averaged local velocity difference between the two phases to determine the relative motion between the phases. Another approach is the multi-fluid modeling technique. This type of modeling differs from separated flow in that the two-phases are described in separate conservation equations written for the liquid and vapor phases (9). As an alternative to the mentioned modeling approaches, mechanistic models have proven to be the most accurate in predicting the geometric and fluid property variations (10-12). This is a hybrid approach where physics-based methods are merged with data-driven method to develop the so-called “Hybrid Model”.

In two-phase liquid-gas flow, the crude oil and water during transportation are considered as a well-mixed fluid (13-14). In this case, the water is totally entrained in the oil phase and pipeline internal corrosion is mitigated. However, this is only true for flow conditions with relatively low water cuts. As water cut increases, a change in the emulsion structure occurs resulting in the separation of water from the oil continuous phase. This permits water to come into contact with the pipeline steel surface, which will trigger corrosion. In addition to water cut, crude oil properties (density and viscosity) and production environment (e.g. mixture velocity, pipeline inclination) are also major factors affecting the oil-water mixture flow pattern.

**Steady State Multiphase Flow Patterns for Oil-Water Mixtures**

Several theoretical and experimental studies have been conducted to model and identify the oil-water flow pattern transition (13, 14). The results show that the flow pattern in oil-water mixture is directly related to water fraction, mixture velocity and oil viscosity. Based on the degree of mixing, the two-phase flow patterns can be classified as (15):

- **Stratified flow:** Both liquids flow in separate layers with no mixing at the interface. This usually happens at low velocities.
- **Semi-mixed flow:** Some mixing of the liquids occurs as the velocity increases. Different sub-patterns such as semi-segregated, semi-mixed and semi-dispersed can be found in this flow pattern (16).
- **Dispersed flow:** Homogeneous flow pattern that can be either oil dominated (water-in-oil emulsion) or water dominated (oil-in-water emulsion).

When the flow is oil-dominated (i.e. the water is totally entrained as droplets in the crude oil flow), the contact between the corrosive element and the pipeline steel surface is avoided and the corrosion risk is eliminated. Whilst, in the stratified flow conditions, the water layer is in continuous contact with the bottom part of the pipeline. With complete water wetting of the pipeline bottom surface, higher corrosion risk becomes more ubiquitous. For flow patterns where the water/oil wetting is intermittent, localized corrosion behavior can be observed. This aspect is beyond the scope of this article; however, its importance and coupling to the corrosion rate needs to be identified and addressed.

**DATA DRIVEN MODEL (DIGITAL TWIN) FOR CORROSION PREDICTION**

The idea of representing physical processes with mathematical expressions is widely used in many industries, especially in the oil and gas industry, to provide insights to the underlying fundamentals. Mathematical models are an intermediate that allows an avenue to interpreting and judging gathered information from many physical-chemical systems. This provides insight into how this information correlates to describe and predict output behavior. In addition, this helps engineers to make reasonable decisions concerning the design, control, and the recalibration of systems under certain operational criteria.

The design of flowlines, pipelines, or any transmission line system carrying organic fluids is a key consideration for the construction of safe and reliable production and transportation systems. Hence, while designing oil and gas production and transmission systems, an engineer needs to be aware of the importance of a number of factors and physical-chemical phenomena which can have serious ramifications. Another major contributing constituent (e.g. besides water) to higher corrosion rate is carbon dioxide (CO2), which is present throughout the oil and gas extraction process. The combination of water and CO2 forms a consequential corrosive force, since in the presence of water, CO2 will react to form carbonic acid (H2CO3). The interaction of the H2CO3 with mild steel, initiates a corrosion process that results from a charge exchange gradient between the two substances. If left unchecked the structural integrity of the transmission line could be compromised. Therefore, a reliable corrosion rate predictor is required during the design phase to help ensure the appropriate materials and dimensions are selected, and that there is sufficient planning, monitoring and system control in place. Being able to generate accurate corrosion rate estimations will help avoid system component failure, prevent HSE incidents, and, reduce costs.

The theoretical fundamentals of the carbon dioxide corrosion process can be classified into three major categories: 1) mechanistic, 2) empirical and 3) semi-empirical models.

- Mechanistic: These models are built to give a clear description of the mechanisms behind the governing electrochemical reactions producing the corrosion process. Therefore, most of the parameters have a realistic physical meaning.
- Empirical: These are basically mathematical expressions and equations with no real significance to physical meaning. The main expressions constructing these models are usually chosen arbitrarily and are used to extrapolate the results for a wider range of experimental database, but this doesn’t always lead to reliable results.
- Semi-Empirical: These models have some independency to the electrochemical fundamentals of the CO2 corrosion process. They are mainly used where the theoretical knowledge is insufficient and mathematical and empirical expressions are required.

**Fundamental Background of CO2 Corrosion Process**

The CO2 corrosion process involves different chemical equilibriums. These relate mainly to anodic iron dissolution in an acidic solution, with cathodic reaction of hydrogen from water. This electrochemical reaction occurs when the metal surface is exposed to the electrolyte (corrosive solution). This condition launches a mass transfer process ensuring that the metal anode at the anode site loses electrons, which are then absorbed by other metallic atoms at the cathode site in order to balance the positive and negative charges, as shown by Equations 1 and 2.

\[
\begin{align*}
F_e + CO_2 + H_2O & \rightarrow FCO_2^+ + H^+ \\
F_e & \rightarrow F^{z+} + 2e^{-}
\end{align*}
\]

However, these reactions do not reflect the true complexity of this chemical process. Hence, understanding the variety of electrochemical
Mathematical Modeling of CO₂ Corrosion of Mild Steel

Mechanistic models are highly dependent on the physical-chemical processes underlying the corrosion process. The structure of these models is to build a physical understanding of the mechanisms governing the electrochemical aspect occurring during the exchange between the metallic surface and the corrosive solution. Many researchers developed mathematical models that attempted to give a precise description of the different electrochemical reactions. The first model proposed assumed that the iron dissolution process is given by a multistep mechanism, which attempts to correlate the effects temperature and partial pressure of carbon dioxide gas on corrosion rate [19].

Several revisions were made to the proposed model to assure better accuracy. These revisions led to numerous correction factors to take into account the different phenomena influencing the carbon dioxide corrosion process.

Empirical models are less dependent on theoretical principles. Also, any attempt to modify their structure, on the basis of new knowledge, is quite difficult; hence, new correction factors are used to take into account new effects influencing the corrosion process. One of the most widely known empirical models for carbon dioxide corrosion rate prediction is the NORSOK model. This has been widely used as a free open standard model for corrosion estimation. This standard is based on the semi-empirical corrosion model developed by DeWaard et al. [20], which was derived from the same experimental database used DeWaard and Milliams [19]. This model was constructed on a temperature dependent function multiplied by a number of correction factors. These factors take into account the effect of the partial pressure of carbon dioxide, measured pH level, fluid flow velocity, steel composition, and a protective scale formation layer.

\[
(4) \quad CR_{act} = K f(P_{CO2}) \int f(pH)\]

Semi-empirical models have some dependency on electrochemical fundamentals of the CO₂ corrosion process. They are mainly used in cases where the theoretical knowledge is insufficient in a particular area of study, and both mathematical and empirical expressions are required. These models are calibrated to a wide range of reliable data which make the interpolation of results more accurate, although the extrapolation of these results could lead to unrealistic values. The DeWaard and Milliams corrosion model is the most widely used, and it presents a basis to develop new semi-empirical models. Improvements were made to the starting model structure by recalibrating coefficients based on new experimental data by DeWaard, Lotz and Milliams [20].

\[
(5) \quad \log_{10}(CR) = 7.90 - \frac{2320}{T} - 5.5 \times 10^{-7} T + 0.67 \log_{10}(f_{FeCO3})
\]

This model was also recalibrated by adding correction factors that take into account the impact of a protective film of FeCO₃ on the corrosion rate. One other major improvement captures the effect of velocity in the absence of protective scaling; this was proposed as a parallel resistance model.

\[
(6a) \quad \frac{1}{CR} = \frac{1}{CR} + \frac{1}{CR}
\]

\[
(6b) \quad \log_{10}(CR) = 4.93 - \frac{1.19}{T} + 0.58 \log_{10}(f_{FeCO3})
\]

From the analysis, the DeWaard-Lotz-Dugstad model gave the best prediction performance. Since the experimental conditions presented in Dugstad et al. only considered condensed aqueous environments, the effect of pH was not included. Therefore, the idea was to mathematically introduce the effect of the pH and the mixture flow velocity to the activation reaction related term presented by the DeWaard-Lotz-Dugstad model. This was accomplished with the introduction of a “Linear Parameter Varying” model to augment the original structure, therefore, modifying the DeWaard-Lotz-Dugstad model [21]. The modification introduced rewrites the first term of the model using a new set of varying constants, which had a dependency on pH and flow velocity values.

\[
(7) \quad \log_{10}(CR) = a_0 + a_1 \frac{pH}{T} + b_0 + b_1 U + b_2 pH \log_{10}(f_{FeCO3})
\]

To obtain accurate estimation results, the goal was to reduce the prediction residual. The change in the model’s constants was achieved by investigating the prediction residual, switching the emphasis to a residual reduction problem. This was solved by modeling the prediction residual and developing a linear model using linear regression techniques such as Least-Square Estimation. This allowed the approximation of the prediction results using a linear correlation which introduced pH and flow velocity measured values. This provides the ability to express the influence of these variables on the corrosion rate prediction and their effect on the electrochemical exchange underlying the CO₂ corrosion process. The process followed is shown in Figure 1.
The results of the training phase, shown by Figure 2, detail the accuracy improvement of the recalibrated model after the modification of the constants with the varying parameter method. The major enhancement offered by the recalibration process is clearly shown, compared to the DeWaard-Lotz-Dugstad model (2), which does not predict very well (rate values beyond 20 mm/yr.).

Upon further investigation, the measured corrosion rates at these points were measured under conditions where the pH values were low and the flow velocity values were high. This observation enhances the need to investigate the effect of the variation of these two parameters on the prediction from the model. The LPV model allows for a more complete modeling of the CO₂ corrosion process. The new LPV model for CO₂ corrosion prediction has shown very good performances when compared to other data-based models that presently exist. The prediction results were very close to the experimentally measured corrosion rates, and the estimation error was reduced by 80 percent. This ensures greater accuracy that might be coupled with multiphase flow models to enable precise corrosion rate prediction in oil and gas production and transmission systems. This lends itself to the creation of a digital twin that might help to combined multiphase flow regimes with erosion mechanisms and CO₂ corrosion processes.

DIGITAL TWIN: WORKFLOW AND TEST CASE

Multiphase flow characteristics significantly affect the corrosion process of the steel pipelines in the oil industry. Presented in this section is a simulated case study for the model-based design of subsea architecture based on predicted corrosion rates. The oil and gas production from four different wells is grouped through a subsea manifold, which feeds the riser through a long production pipeline (Figure 3). The properties of gas and liquid phases, operating conditions and pipeline design parameters, namely the jumper and production pipeline diameters, are captured in Table 2.

A digital twin is developed to mimic the steady state and dynamic behavior of the real subsea architecture. A physics-based model is derived for each subsea component, which is modeled using first principles. The models are then brought together and implemented in a MATLAB simulation environment. Next, the subsea architecture digital twin is integrated with the steady-state multiphase pattern (22) to estimate the flow properties in the four jumpers and the production pipeline given the various scenarios. Finally, the results are used to estimate corrosion rate based on the proposed corrosion model.

The subsea architecture digital twin is simulated for different pipeline sizing scenarios. For each simulated case, the liquid-gas two-phase steady-state model estimates the liquid and gas flow rates. The resulting liquid velocity serves as input to the proposed LPV model to predict the corresponding corrosion rate. Illustrated in Figure 4 are the predicted corrosion rates of the four jumpers and the production pipeline for 1 percent gas-volume-fraction two-phase flow. Results suggest that the corrosion rate in jumpers can be reduced by increasing jumper diameter and decreasing production pipeline diameter, whereas production pipeline corrosion rate can be reduced by decreasing both jumper and production pipeline diameters. To optimize the subsea architecture based on minimizing the average corrosion rate of both lines, the optimal diameters are found to be 0.125 m and 0.23 m for the jumpers and the production pipeline, respectively. An investigation of the effect of the production fluid gas-volume-fraction on the system corrosion rate is also conducted. Figure 5 presents the relationship between the gas-volume-fraction and the corrosion rate of the optimized subsea architecture lines. It can be concluded that corrosion rates can be mitigated by an increase in the gas-volume-fraction in the production fluid.
CHALLENGES

Uncertainties and Limitations

Digital twins are mathematical representations of experimental observations. Digital twins that are based on data analytics created from machine learning and deep learning algorithms seek these mathematical representations from an input-output fidelity (systems) level. This means that machine learning solutions are not necessarily unique. Thus, predictions outside the dataset input range cannot be inferred nor estimated based on such models. Physics based models on the other hand can be used for output predictions with a mathematically rigorous quantification of the uncertainty for these predictions. Physics based models, including mechanistic based models as is the case for this study, also have prediction challenges. Consider the experimental corrosion rates reported in the literature (Table 3).

Table 3 contains the measured corrosion rates taken from Dugstad et al. [21]. Part of the results contains duplicate testing conditions. Notice the significant uncertainty observed for specific experimental conditions. These uncertainties are mainly due to high temperatures, high velocities and/or low pH, all of which represent favorable conditions enhancing high corrosion rates. For the models presented in this work, the average corrosion rates were used. Therefore, there is a need to perform a design-of-experiments enabling independent validation of the model along with a quantification of the uncertainty to ensure robust accuracy from the model.

Now consider the case of the CO₂ corrosion process where scale formation on the surface of the metal was not considered. The increase of total pressure will lead to an increase of the CO₂ partial pressure, which typically results in an increase of the corrosion rate. However, according to literature data [22], for the case of high pressures, the authors recorded corrosion rates that tend to stabilize between 5 and 20 mm/year. This observation could be explained by the fact that for some favorable conditions when high pH and high pressure values are present, supersaturation of bicarbonate and carbonate ions are higher due to their increasing concentrations. This in turn accelerates the carbonate precipitation to create a protective film that reduces the tendency for CO₂ corrosion to occur. Taking into considerations the effect of the scale formation will ameliorate the corrosion rate prediction and enhance the utility of the model during the design and dimensioning process of the transmission infrastructure.

Internal pitting corrosion is also one of the most influencing factors in the degradation and failure of the pipeline. This type of corrosion occurs when the metal is exposed to a solution中含有 both chloride and sulfuric acid. The mechanism involves the formation of microAILS which can reach high temperatures and high velocities, promoting high corrosion rates. For the models presented in this work, the average corrosion rates were used. Therefore, there is a need to perform a design-of-experiments enabling independent validation of the model along with a quantification of the uncertainty to ensure robust accuracy from the model.

Table 2  Study case parameters

<table>
<thead>
<tr>
<th>Fluid Properties</th>
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<tbody>
<tr>
<td>Liquid density</td>
<td>900 (kg/m³)</td>
</tr>
<tr>
<td>Liquid absolute viscosity</td>
<td>1.5E-3 (Ns/m²)</td>
</tr>
<tr>
<td>Liquid bulk modulus</td>
<td>1E00 (Pa)</td>
</tr>
<tr>
<td>Gas density</td>
<td>240 (kg/m³)</td>
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<tr>
<td>Gas absolute viscosity</td>
<td>1E-5 (Ns/m²)</td>
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<td>Gas volume fraction</td>
<td>(1-50) [%]</td>
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<table>
<thead>
<tr>
<th>Pipeline Sizing</th>
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<tr>
<td>Jumper length</td>
<td>50 (m)</td>
</tr>
<tr>
<td>Production pipeline</td>
<td>10000 (m)</td>
</tr>
<tr>
<td>Jumper diameter range</td>
<td>(0.1-0.125) (m)</td>
</tr>
<tr>
<td>Production pipeline diameter range</td>
<td>(0.23-0.28) (m)</td>
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</table>

<table>
<thead>
<tr>
<th>Operating Conditions</th>
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</tr>
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<tbody>
<tr>
<td>System inlet pressure</td>
<td>1E07 (Pa)</td>
</tr>
<tr>
<td>System outlet pressure</td>
<td>1.2E05 (Pa)</td>
</tr>
</tbody>
</table>

Figure 4 Subsea architecture corrosion rate prediction (1 percent gas-volume-fraction case)

Figure 5 Relationship between gas-volume-fraction and corrosion rate (optimized subsea architecture)
of oil and gas production pipelines [21]. It consists of a loss of metal at discrete areas due to localized attacks, causing the penetration of the pipe wall by pits, where the protective film breakdown usually occurs, and its propagation to the surrounding areas, leading to different types of failure (e.g. leakage, burst or rupture). The digital twin challenge is to track these localized attacks and predict corrosion’s occurrence. Such knowledge will offer the possibility to understand the risk of failure of the corroded pipeline, and act properly will offer the possibility to understand the risk of failure of the corroded pipeline, and act properly. The digital twin can also lead to very high fluctuating mass transfer rates (particularly in slug flow), which in turn, can greatly affect the corrosion rate.

Another important factor to consider is the influence of pipe diameter, which affects the corrosion rates in pipelines. It clearly demonstrated the benefit of a digital twin’s ability to predict corrosion rates caused by carbon dioxide and the effect of a multiphase flow regime on its ‘state of equilibrium’. The various flow patterns will lead to a variety of steel surface wetting mechanisms that can strongly affect the corrosion process in the absence of protective scaling. Multiphase flow can also lead to very high fluctuating mass transfer rates (particularly in slug flow), which in turn, can greatly affect the corrosion rate.

One of the main objectives was to establish the ability to create, via the LPV flowchart procedure, a digital twin for CO2 corrosion prediction that is based on newly introduced model coefficients where the fluid factors influencing corrosion rates are entered linearly (e.g. a linear correlation between the pH and the flow velocity). The authors cannot conclusively state that the proposed LPV coefficients are indeed correct. The authors cannot conclusively state that the proposed LPV coefficients are indeed correct. That is, the LPV coefficients were not derived from physics. Instead, a system identification approach was utilized to capture the residuals produced from the DooWaard et al. model. Therefore, the proposed LPV model serves as a starting point where future corrosion rate models could be built. The modularity of the proposed model lends itself to isolated corrections derived from additional experimental and scientific studies that investigate the items presented in this section as well as other items not highlighted here.

CONCLUSION

The proper design of flowlines, pipelines, or any transmission line system carrying organic fluids is of major concern in the oil and gas industry. These designs must ensure reliable production and transportation systems. It’s essential to prevent disastrous types of perturbation that could lead to a malfunctioning of one or more component of these systems. The most complex perturbations, with a significant impact to the reliable and safe transmission of fluids in pipelines and flow lines, is the prediction of corrosion rates caused by carbon dioxide and the effect of a multiphase flow regime on its ‘state of equilibrium’. The various flow patterns will lead to a variety of steel surface wetting mechanisms that can strongly affect the corrosion process in the absence of protective scaling. Multiphase flow can also lead to very high fluctuating mass transfer rates (particularly in slug flow), which in turn, can greatly affect the corrosion rate.

One of the main objectives was to establish the ability to create, via the LPV flowchart procedure, a digital twin for CO2 corrosion prediction that is based on newly introduced model coefficients where the fluid factors influencing corrosion rates are entered linearly (e.g. a linear correlation between the pH and the flow velocity). The authors cannot conclusively state that the proposed LPV coefficients are indeed correct. The authors cannot conclusively state that the proposed LPV coefficients are indeed correct. That is, the LPV coefficients were not derived from physics. Instead, a system identification approach was utilized to capture the residuals produced from the DooWaard et al. model. Therefore, the proposed LPV model serves as a starting point where future corrosion rate models could be built. The modularity of the proposed model lends itself to isolated corrections derived from additional experimental and scientific studies that investigate the items presented in this section as well as other items not highlighted here.

Digital twins are mathematical representations of experimental observations or physics principles. Digital twins based on data analytics created from machine learning and deep learning algorithms seek these mathematical representations. Predictions outside the dataset input range cannot be inferred nor estimated based on such experimentally derived models. Physics based models on the other hand can be used for output predictions with a mathematically rigorous quantification of the uncertainty for these predictions. The LPV corrosion model, used to create the digital twin, is based on newly introduced model coefficients where the fluid factors influencing corrosion rates are a linear correlation between the pH and the flow velocity. Future work will investigate a more developed structure such as non-linear combinations of the input values. One cannot conclusively state that the proposed LPV coefficients are indeed correct. The LPV coefficients were not derived from physics, instead it demonstrates a data driven approach based on a system identification approach. A key aspect is its modularity that lends itself to isolated corrections derived from additional experimental and scientific studies. However, the article clearly demonstrates one avenue for the development of a digital twin, which, if constructed cleverly, will enable the descriptive, predictive, diagnostic, and prescriptive analytics that provides value-add to the oil and gas industry.

<table>
<thead>
<tr>
<th>T[°C]</th>
<th>P(MPa)</th>
<th>U(m/s)</th>
<th>pH</th>
<th>Experimental Corrosion Rate (mm/year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>60</td>
<td>0.22</td>
<td>13</td>
<td>3.8</td>
<td>Max Value 44, Min Value 32, Average Value 38</td>
</tr>
<tr>
<td>90</td>
<td>0.37</td>
<td>3.1</td>
<td>3.8</td>
<td>Max Value 17, Min Value 16, Average Value 16.5</td>
</tr>
<tr>
<td>21</td>
<td>1.4</td>
<td>3.1</td>
<td>3.6</td>
<td>Max Value 15, Min Value 6, Average Value 10.5</td>
</tr>
<tr>
<td>21</td>
<td>2.1</td>
<td>3.1</td>
<td>3.5</td>
<td>Max Value 38, Min Value 15, Average Value 26.5</td>
</tr>
</tbody>
</table>

Table 3: Experimental Corrosion Rate
REFERENCES


3. Medium: X; Size: pp. 15, Paper 128


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