Originally appeared in World Oil® JANUARY 2019 issue, pg 51-54. Posted with permission.

DIGITAL TRANSFORMATION

Artificial intelligence drives early-warning alerts to prevent ESP disruptions

Artificial intelligence may seem like a solution in search of a problem, but an on-line retailer has used it since 2006, helping to grow sales by 1,600%. It's now being applied in oil and gas operations, and it added value in an E&P pilot program with 30 electrical submersible pumps.

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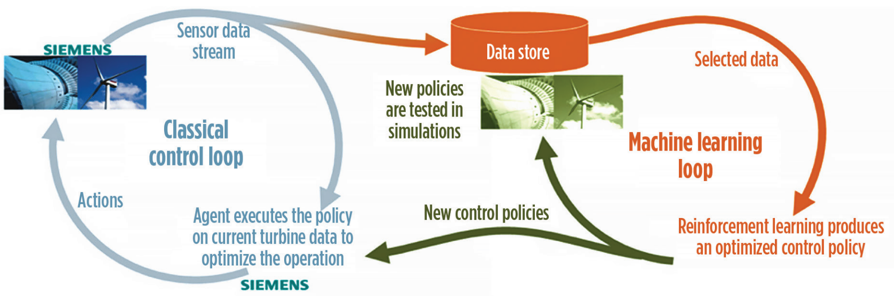
Fig. 1. A traditional automation control loop can be enhanced by machine learning to optimize control policy, to improve asset performance and utilization. A new policy can be tested in simulations of the asset's digital twin before being enacted.



Amazon.com has a valuable lesson for today's E&P operators, who are seeking to address core challenges with various technology solutions. It involves the application of artificial intelligence (AI) to enable customers to cross- and up-sell themselves—no sales representatives are needed. Chances are, many Amazon shoppers have used its AI features without even knowing it.

Now let's consider the E&P challenges that AI can help address. A major goal is to reduce production costs to approximately $10 bbl or less—helping to ensure profitability in virtually every operating environment. To achieve this, many operators are adopting manufacturing models supported by greater electrification, automation and digitalizing. Ultimately, they must maximize operational efficiency and output productivity, which requires boosting performance and utilization of most equipment assets.

Another challenge is the need to refresh an aging workforce. For this, they are automating as many manual tasks as possible. At the same time, they are hiring younger professionals, who are equally comfortable with operational technology (OT) and information technology (IT).

With the integration of OT and IT, companies can increase their operational transparency and visibility. Secure Internet of Things (IoT) connectivity and cost-effective, cloud-based platforms can help them achieve this integration, not only in single-site operations, but across multiple locations around the world, even in extremely remote regions.

LOST OPPORTUNITY

Despite hundreds of billions of dollars in E&P technology investments, experts agree that data in operations remain a mostly untapped asset. An offshore platform may have as many as 80,000 data tags, yet most of it is siloed, fragmented and isolated in various systems, databases, and even individual spreadsheets.

In effect, much of these data that are being generated don't go far, nor do they provide but a fraction of the operating insights that they could for decision support, performance optimization, predictive maintenance, and other enhanced capabilities. That's because the sources are sensors on various tools, the OEMs making them, if not the rig owner and lessor. These data get further fragmented and isolated, and are transferred to spreadsheets on individual PCs and historian servers that often become their final repositories.

What's missing is a "single-source-of-truth" that can provide up-to-date, enterprise-wide views, so users can view all their company's operational data and drill down to granular levels to view specific parts of an operation. But promising to change this situation, and transform how E&P gets done, are advanced analytics coupled with AI and a specific application of the latter called *machine learning*, which will be explained in more detail. In turn, cloud-based data lakes can be used as a single store of all E&P data, including raw operational data and transformed data, used for tasks such as analytics and machine learning, plus reporting and visualization.

DELIVERING VALUE

Artificial intelligence is already deployed in many industries, and its applications are spreading quickly. One online company helped to pioneer its commercial application in consumer retail, back in 2006, when it introduced an AI-driven cross- and up-sell feature to its web pages. Readers who use Amazon.com might be familiar with its feature phrase "customers who bought this also bought" which suggests items to complement and add value to the purchases they might be making.

This feature, alone, reportedly boosted Amazon sales in the first year by 35%. Since then, the company's growing use of AI has helped drive its revenues, making founder Jeff Bezos the world's wealthiest man. In 2017, a report revealed that its AI-driven product recommendation engine was responsible for 35%—or about $62 billion—of that year's revenue, which was nearly $178 billion.

Fig. 2. Components and data flows within the predictive maintenance model.

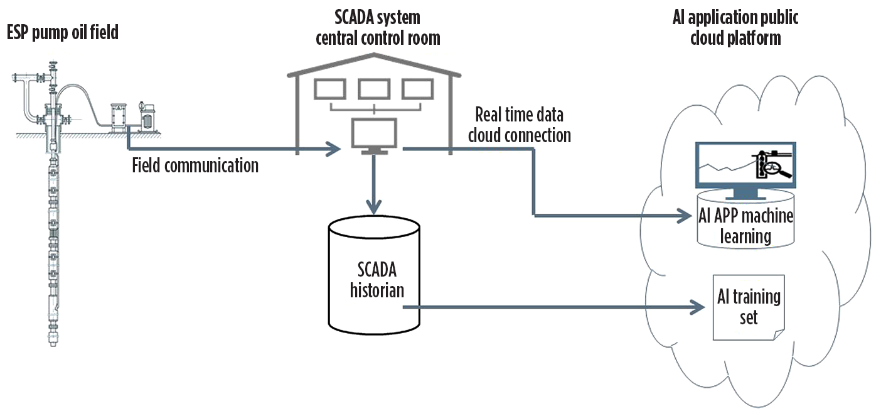
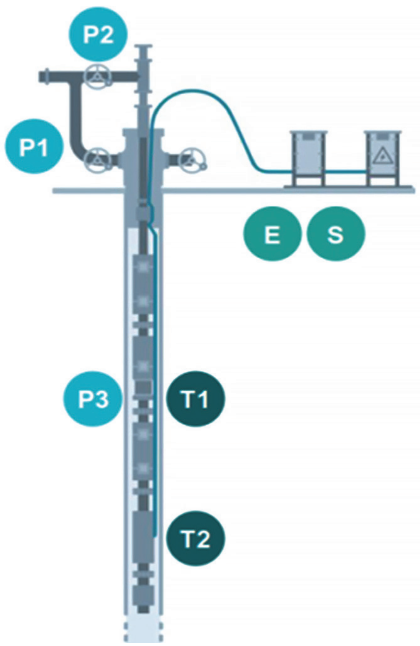


Fig. 3. Process variables monitored in the ESP.



Transferring technology to other industries. While Amazon.com serves as a well-known example of putting AI to work and achieving excellent results, many other examples exist, some with help from Siemens data scientists. The CERN Large Hadron Collider, the world's largest and most powerful particle accelerator (and the world's largest and most complex machine), uses AI-enabled pattern recognition to reconstruct particle tracks. By applying machine learning, these data scientists aim to facilitate up to 20 times more particle collisions than are currently possible.

AI and machine learning are also being employed in high-speed trains, steel-making, and power generation to improve asset performance, visibility, availability and reliability, Fig. 1. Applications of these technologies are fast becoming practical and transformative, given their capability to extend human cognition, or conduct tasks that are beyond humans. And they are nearly ready for E&P deployments.

In these other industries—with full applicability to E&P—these technologies are being integrated with so-called *digital twins.* These are 3D virtual proxies for their physical counterparts, whether those are components, subsystems, complete machines, or conceivably, the entire topsides of an offshore platform and its underwater operations, all the way downhole to the drill bit.

Digital twins are derived from CAD, CAE and CAM software tools used to design them. They can be used for virtual commissioning and full lifecycle management, with secure IoT connectivity delivering performance data to continually update them. Performance optimization and issue resolution simulations can be conducted anytime, without disrupting the physical counterpart.

ESP MONITORING

Siemens recently conducted a pilot deployment of AI in 30 electrical submersible pumps (ESP) operating in a single onshore field. The pilot showed how using AI, with data-driven analytics, can be employed in a predictive maintenance model to boost availability and prevent disruptions from forced outages.

The ESP application is a starting point for adapting AI from other industries, starting with horizontal applications (across different industries) to vertical applications (specific to the E&P industry) that can be coupled with automation and enterprise resource planning (ERP) systems.

KEY AI CONCEPTS

Artificial intelligence generally refers to the use of computer technology to do work that typically requires human intelligence and learning ability. One example is pattern recognition, whether in data or in images, speech or music, and simple decision-making. AI powers personal digital assistants, such as on smartphones and in-home devices, as well as inference engines, such as what online shopping services use to cross- and up-sell their clients.

Conceptually, AI is rooted in machines that were designed to think, understand and solve problems, just like humans. Next, computational models emerged, called neural networks, that sought to replicate the human brain's many trillions of synaptic connections, but they lacked the processing power for applications outside academia.

Changing times, converging technologies. That's changed in recent years. Diverse technology trends have converged to make AI not only possible but practical. Among them: relentless cost reductions in computer processing power; advanced statistical tools for big data analytics; parallel processing computer architectures available via dial-up, pay-as-you-go access; low-cost flash storage, able to handle huge data sets; ultra-fast networking between computing and storage resources; and public cloud platforms, making these other resources more accessible and cost-effective.

Then there are the data that fuel AI applications, with machine learning chief among them. The latter runs data through various statistical models to find patterns that would be invisible to humans. It then effectively "learns" from the data and adapts its algorithmic functions without any human programming. That's why the more data processed by an AI application, the smarter the app becomes.

With machine learning, users can discover what they don't know—and quantify better what they think they know. How? When operating, these applications search nonstop for patterns in, say, a stream of a billion data points per second that are simply undetectable by human perception. Often, what people think they know isn't supported by the associated data. And pattern recognition can deliver new insights.

Providing decision support. In E&P operations, an AI-enabled, machine-learning application could detect an unexpected pattern in sensor data streaming from a critical asset. The anomaly might signal an imminent bearing failure, an abnormal vibration, or a sticking valve, prompting an investigation.

Given pre-programmed rules, the application could trigger an alert to dispatch a maintenance technician, who can be given a preliminary diagnosis, instructions on fixing the problem, and even have spare parts identified, pulled, and waiting. A workflow can be designed as follows, with an AI-enabled application:

- **Detecting an impending failure** of an operating asset.
- **Identifying the problem's origins** using pattern recognition and root cause analysis.
- **Dispatching a technician** and issuing an automated spare part order.
- **Closing the loop** by entering the finished maintenance job into a database log and updating the analytical models with any new information (from the technician or the sensor data).

Or, based on their expertise and experience, wellsite engineers can acknowledge the alert and decide whether to run a part to failure, then replace it, or wait to change it out during the next planned shutdown. Either way could help them avoid a forced shutdown and the costly production disruption. Conversely, if the issue was a matter of life or environmental safety, they could order an immediate shutdown and avoid injuries or environmental damage.

Liberating human creativity. AI-enabled machine learning can effectively emancipate human operators from many of the menial tasks involved in "wrangling data," the term that scientists use to describe the chores associated with collecting, cleaning and normalizing data. These activities can be enormously time-consuming and keep professionals from doing important creative work, often on projects that can add significant value to E&P operations benefiting the business.

AI-driven workflows, enhanced with machine learning, also can help screen out false-positives and avoid "alarm storms," the latter caused by alerts about non-consequential anomalies of asset behaviors. These are two of the benefits from Siemens continuing to embed more AI into its Drive Train Analytics remote monitoring and diagnostics service for complex turbines and compression trains. This filtering helps focus human attention on important operational issues, especially ones that could disrupt production.

Fundamentally, AI and machine learning are about decision support. It can help engineers and technicians make more informed decisions, in less time. Also, as older employees retire, operators will lose valuable experience-based knowledge and learned intuition about equipment and situations requiring quick decisions. AI and machine learning applications can help fill these gaps, as well as help a younger workforce perform as needed by operation, with greater integration of OT and IT domains.

ESP MAINTENANCE MODEL

As previously mentioned, an ESP pilot project was initiated in 2018 to evaluate AI's ability to detect and address abnormal downhole pump behaviors. It involved 30 ESPs deployed in an onshore field of medium depth. AI supported a predictive maintenance model, which is an early warning system, focused on identifying anomalous ESP behaviors before failure.

The overarching goal was to use AI to enhance ESP availability and utilization while preventing costly production disruptions. After all, when ESPs are deployed, their pump and electrical motor assemblies are positioned downhole and are subject to adverse conditions, especially heat and often abrasion.

In today's ESP deployments, many diagnostic methods exist to assess an ESP's health status, but they typically provide forensic analysis after failures occur. With AI-enabled machine learning behind a predictive maintenance model, operators can learn of changes in ESP conditions in advance, plus actionable intelligence to identify the type of abnormality. This would include an indication of an issue's severity for enhanced decision support. For example: Can the problem be managed until a planned shutdown and avoid a forced outage, or must it be addressed immediately to prevent one?

Predictive model architecture. The pilot's predictive maintenance solution employed a neural network using machine learning, and linked securely to an IoT-based cloud platform, Fig. 2. Key system components are:

ESP. Pumps varied from 200 to 500 kW, and each was connected to a medium-voltage variable frequency drive (VFD) on the surface, powered by a local utility. Each pump's subsurface instrumentation gathered pump condition data, while surface instrumentation provided other operating data.

SCADA system. A centralized SCADA system linked the distributed ESPs via a fiber optic network. Their process data were fed into an historical database, able to receive the high-speed, streaming data.

Neural network. The NN application, enabled with AI-based machine learning, used open-source software and was deployed in an offsite, public cloud platform.

Predictive maintenance application. This was an HTML application deployed in the same public cloud. It was implemented as a stand-alone support system, with no functionally linked to the SCADA system.

An overview and visual key for the main process variables monitored in the pilot project are shown in Fig. 3.

Surface Variables
P1: Annulus pressure
P2: Production oil pressure
E: Motor current (measured at VFD)
S: Motor speed (measured at VFD)
Sub-Surface Variables
P3: Inlet oil pressure at pump
T1: Inlet oil temperature at pump
T2: Pump motor temperature

These variables were sampled at 5-to-10-sec intervals, using the SCADA system's polling mechanism. Their information entered the historical database, with a store-on-change compression scheme.

Preparing the baseline training data set. First, the pilot required a baseline, and normal operating profile of each ESP system. This was done by collecting a sufficient amount of high-quality data over enough time to be valid. Then, historical process data were analyzed to find extended periods of high-quality data without any major discrepancies.

In turn, scientists extracted these information sets and conducted data cleansing and manual evaluation to provide the neural network with a fully optimized baseline training data set. This data set represented one year of each ESP's normal operation.

With a fleet of 30 ESPs, variants among the process variables used for each different type of pump were found. So, ESP types with similar process variables were grouped together, and each was assigned its own operational model and training data set.

Next, the project team developed a generic, multi-layer, neural network with the AI-based machine learning software. Then, they used the different data sets to train each neural network assigned to a specific ESP variant group.

Failure identified before it occurred. The pilot then used the neural network to conduct data-driven analytics to differentiate normal ESP operational behaviors from abnormal ones. The neural network's anomaly detections and predictions were verified against actual events in the historical data. Events also were verified from additional information drawn from existing operator logs and expert systems used to record ESP failure events.

Once trained, the neural network did identify abnormal ESP behaviors, which were verified against the records of actual ESP historical events. After multiple experiments helped to fine-tune the system, it was able to use the anomalies to make early, probabilistic predictions of ESP failure. In one test, the neural network noted ESP operational anomalies as early as 12 days before its failure.

The pilot project validated the use of AI-based machine learning as a way to empower the ESP predictive maintenance solution—and, importantly, offer operators better decision support, as mentioned previously. After months of testing, the pilot's predictive maintenance solution showed that the system could detect not only multiple types of anomalies known to experienced ESP operators, but also unknown ones that were more complicated and previously undetectable.

PRACTICAL E&P DEPLOYMENT

Some new technologies are undeserving of the hype they generate. But AI and machine learning are not such technologies. Their successful and growing number of deployments in one industry after another shows their practicality.

What's more, as the ESP pilot proved, these technologies are ready for use in the E&P industry, in its drive to become profitable in all market pricing environments. They also can help address the need to refresh an aging workforce and free up staff for more creative and strategic endeavors.

The convergence of different technology trends, especially cloud-based platforms supported by secure and nearly ubiquitous IoT connectivity, is helping to enable the consideration of sophisticated technology solutions, such as AI and machine learning, for E&P operations. But, in most cases, operators, their OEMs, and other suppliers will lack the AI expertise and experience to effectively design, engineer and deploy these kinds of solutions. That's why it's important to engage a well-qualified partner and start with small, well-defined projects, then extend their reach as success is achieved. WO

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