Intelligent Platforms to Manage Offshore Assets

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INTRODUCTION

For offshore oil and gas platforms and other complex petroleum industry facilities, the focus of intelligent asset management usually includes some form of real-time equipment monitoring. A relatively high level of capability maturity has been achieved by both offshore operators and rig owners in terms of monitoring subsurface flow and production equipment (Oberwinkler and Stundner, 2005). Advanced applications of artificial neural networks (ANN) have been used for processes such as gas lift optimization and reservoir modeling. In some cases predictive analytics have been applied to attempt to optimize spending on proactive vs. reactive maintenance work orders (Figure 1).

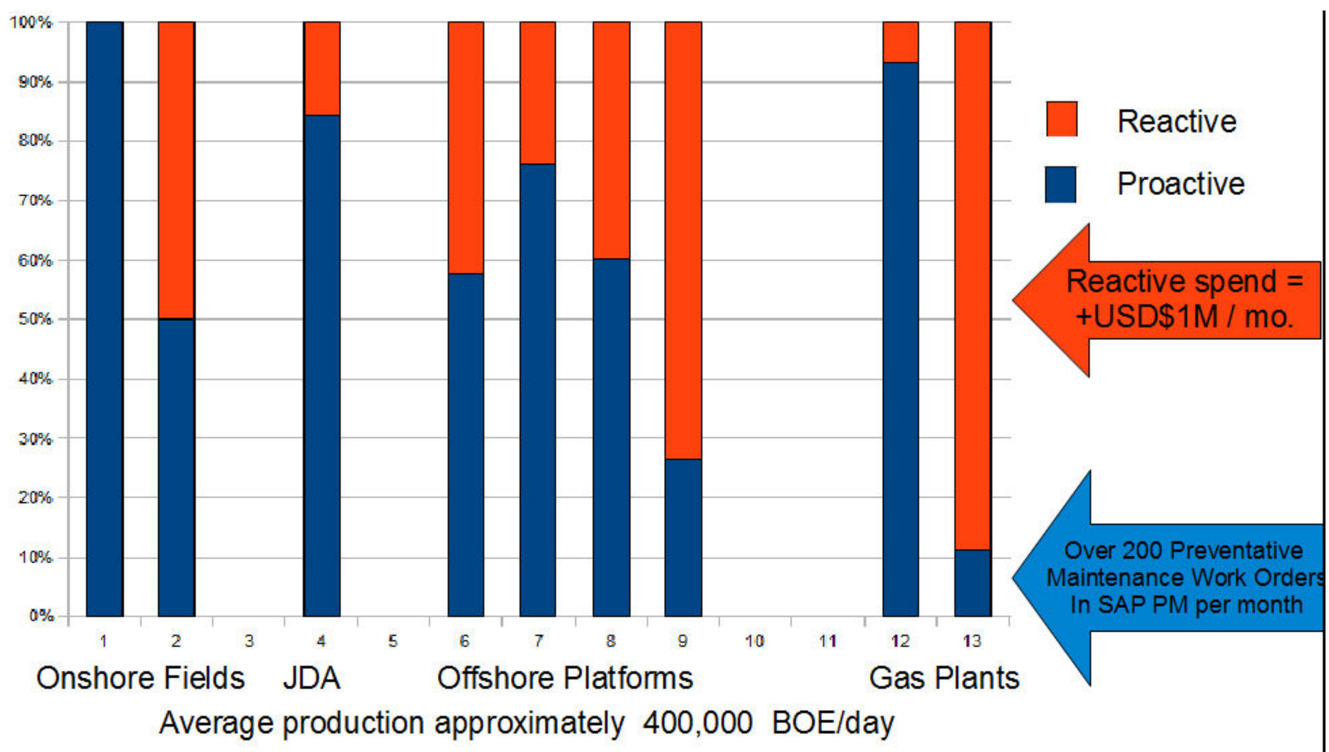

Figure 1: Example range of proactive (blue) vs. reactive (orange) maintenance spend for a group of onshore and offshore oil and gas production assets.

BUSINESS CASE

Despite active and industry standard tracking of such Key Performance Indicators (KPI's), reactive maintenance spend, that is, spending to fix equipment after an uplanned downtime incident, can be as much as 85% of total work order spending for older operational assets. The I-Platform application provides timely threshold alerts enabling either proactive replacement of equipment at remote locations before downtime events or continued operation under optimum conditions, avoiding unnecessary non-productive time based on arbitrary maintenance schedules. Practical applications include extending the time between maintenance cycles based on actual or predicted increases in Mean Time Between Failure (MTBF) for critical equipment components, based on data mined from a global database of performance for similar components in similar operating environments, and vetted with input from industry Subject Matter Experts (SME's). By delaying routine maintenance and allowing more working cycles before taking a system down for work, rig owners can maximize income from Service Level Agreements (SLA's) based on productive time (Figure 2), and avoid costly unplanned downtime that could impact day-rate revenue. With rates for deepwater rigs in the Gulf of Mexico averaging approximately USD$400,000 per day, this is a powerful business case. Alternatively, receiving indications that critical maintenance or replacement is imminent based on the proven predictive capabilities of the ANN can similarly avoid costly downtime events by recommending work orders based on trends in historical and real-time data. Other recent case studies point to cost savings from avoiding regulatory penalties for emissions above Environmental Protection Agency (EPA) standards in the U.S. Gulf of Mexico, and increased production from keeping Electric Submersible Pumps (ESP) in service (Dunham, 2009) and determining the best strategies for staging spares. In the case of ESP failure modes, the objective is to extend ESP run life from 180 to 720 days, decreasing workover costs by 4%, or over USD$20 M per year.

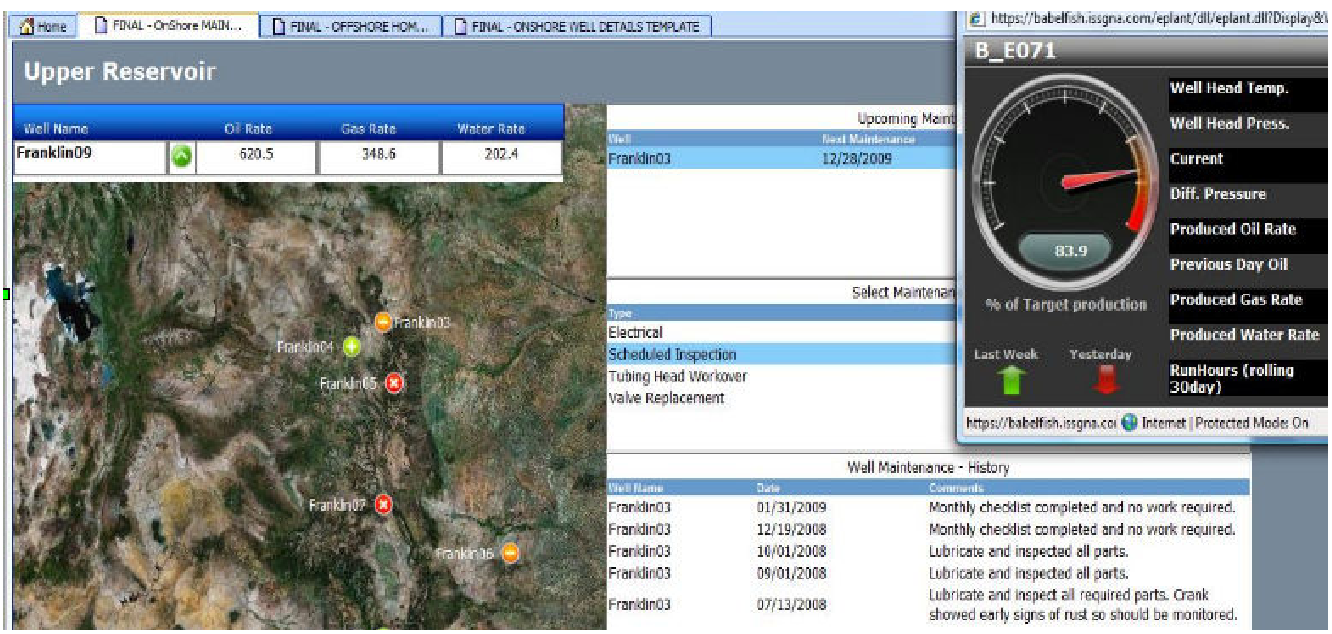

Figure 2: Example of predictive notification for pending maintenance or replacement for oil and gas field operations.

A recent Society of Petroleum Engineers (SPE) Digital Energy Workshop used example production rates, product and personnel cost, operating expenses and implementation timelines to determine that I-Platform deployments could achieve a net cost payout in as little as 3 months and achieve Returns on Investment (ROI) of over 2000% (Farid, 2010). A survey commissioned for the workshop found that for 41 case studies selected from 105 candidates for their factual data on value received from real time data, more than one-third (36.6%) reported value in terms of increased well production (Figure 3).

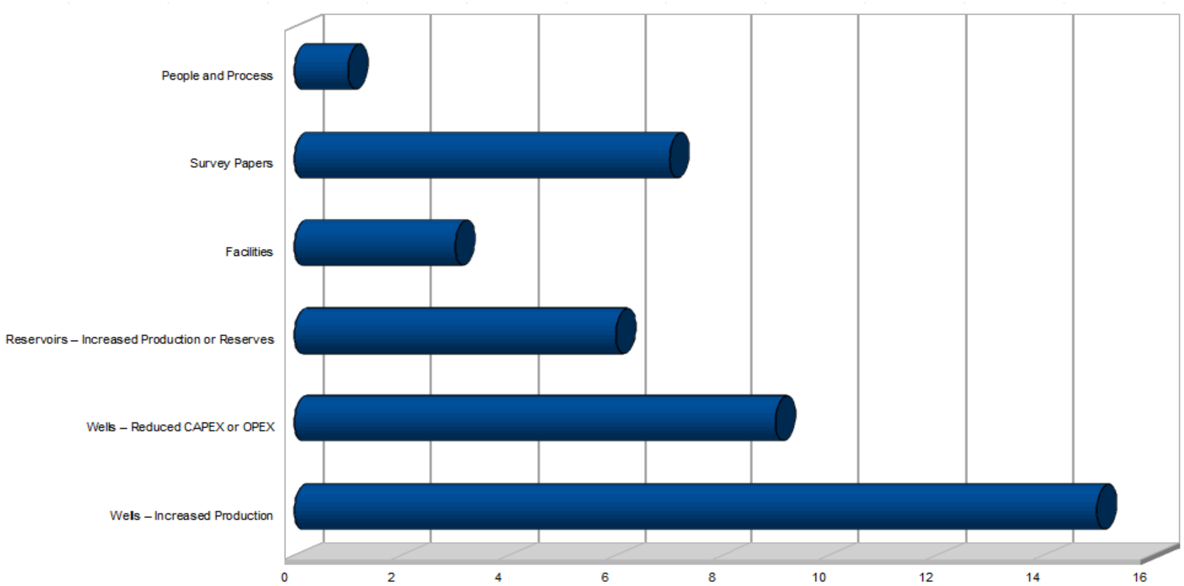

Figure 3: Business cases for real time data optimization from the SPE workshop

Reported gains from using real-time data include a 1% increase in production using advanced collaborative environments for BP in the UK Continental Shelf, amounting to approximately 7,800 BOED (Goodwin et. al., 2010), Shell's realization of at least USD$3 billion in value from the implementation of digital oilfield tools and technologies around the world (Perrons, 2010), Saudi Aramco's capability for co-mingling real-time surface and reservoir data to enable continuous real-time mapping of isobaric data that previously took 6 months to generate (Khamis et. al., 2009), and BP Trinidad using field optimization to improve condensate production by 7%, or 1900 BOPD, and add 4 Bcf to proven reserves (Ramdial et. al., 2009).

While a great deal of focus and technology has been applied to subsurface production equipment on such operating assets, one area where the oil and gas industry falls behind other technology-intensive segments such as aircraft and processing plants is in proactive monitoring of surface equipment. One study (Athens Group, 2009) recently showed that up to 20% of the non-productive time (NPT) experienced by a deepwater rig can be the result of control system failures on drilling or production equipment. But similar failures can impact the fixed surface equipment on the rig floor that can also shut down drilling or production operations. Effective monitoring, maintenance and management of the complex, software-dependent control systems from multiple equipment vendors on the rig floor can be a major determinant of productivity for intelligent platform (I-Platform) implementations (Figure 4).

Primary business drivers for an intelligent platform solution can be categorized as reduction of both equipment downtime and personnel-on-board (POB) requirements, and attendant measurable increases in reliability, safety, regulatory compliance and environmental responsibility. Systems that impact these KPI's can include propulsion, power generation, emissions, marine integrity, and ballast compensation.

Figure 4: Typical KPI dashboard for subsystems of an offshore oil and gas production platform.

METHODOLOGY

The methodology adopted by intelligent platform deployments is to use proven analytic techniques such as self-organizing maps and cascade-forward back propagation ANN to provide predictive modeling using historical and real-time data streams from multiple sensors on the operating asset. In many cases, the data streams from SCADA and other Process Logic Control (PLC) interfaces are already being collected, aggregated and transmitted to shore for the critical surface equipment. However, many operators and service companies report that the sheer volume of data is often so overwhelming that regular or rigorous analysis is not performed, and key diagnostic conditions that may be precursors may be overlooked before a critical failure or incident (Palmer, 2010).

In an intelligent platform solution, data streams from a real time historian (RTH) database and operating envelope data from the equipment manufacturers are used as as a feed directly into each layer of the neural network. As a result, the network is able to model nonlinear relationships using up to fourth-order polynomials. The back propagation indicates that all functions used in the network are both continuous and differentiable which means that the error between the actual and expected results can be used to train the network. Running these types of functions against test data provided by operators generates an error vector in the neural network workspace. The vector contains the calculated error between the actual and simulated dependent data streams, based on test data that was not used in the neural network training. Thus it accurately describes the model's ability to predict output parameters based on multiple aggregated input data streams. In initial tests with actual data from offshore operating platforms, standard deviations on this vector have been calculated at 5.16 with a mean of 0.27. Recent projects have identified areas where offshore operators can gain operating efficiencies by using artificial intelligence tools such as neural networks and self-organizing maps to deliver key performance indicators based on manufacturer's operating specifications and actual equipment performance history (Figure 5). Current predictive capabilities for examples of mono-nitrogen oxides (NOx) emissions from power generation equipment are in the hour to day range, but the trends produced by the ANN show that with sufficient historical data from a range of operating environments, this could be extended out to weeks or months.

Figure 5: Actual (blue) vs. predicted (green) output for a test data stream from an offshore operating plaform.

One example of a practical use of this technique would be to optimize the operating levels of power generation equipment while maintaining environmental emissions below a regulatory mandated upper threshold. One of our early tests with field data used data streams such as generator output, operating temperature, cooling pump performance and battery voltage to effectively predict levels of nitrogen oxide (NOX) emissions on an offshore platform. Over 6000 input data sets were used to train the model, providing the operator with the necessary information to plan and implement procedures for moving a drilling rig between areas of the Gulf of Mexico with different state-regulated emissions guidelines. Previous to the ANN analysis, this data had been collected in spreadsheets and multiple disparate data base formats, but not rigorously evaluated with analytic numerical techniques.

Defining operating envelopes that optimize equipment usage for costs and efficiencies allows early identification and intervention for pending equipment outages and enables root-cause failure analysis that takes into account multiple environmental factors. Since the use of similar intelligent platform technology has already been proven for subsurface drilling and production data streams and has reached a competent level of capability maturity (Heiberger, 2009), there has been more recent interest in extending these capabilities to surface rotating and reciprocating equipment data streams. Another recent industry survey (Benwell, 2010) concluded that since individual equipment vendors rarely understand how a failure in another vendor's system impacts theirs and since they have no control over the availability of other vendor personnel or the configuration of other vendors' systems, the ability to combine actionable data streams from multiple equipment subsystems will be one of key requirements for software-specific risk mitigation and problem remediation services.

Results of the data mining and analysis are delivered in a role-based and easily configurable visual dashboard for multiple aggregated data streams. A recent prototype installation utilizes data streams from a major offshore drilling contractor with a versatile fleet of mobile offshore drilling units and an operational performance center at a leading oilfield service company to demonstrate the viability of this approach for both offshore and remote onshore operations. The success of this proof of concept demonstrates that disparate data from multiple equipment vendors can be gathered from remote locations, analyzed and distilled into actionable items, transmitted across existing infrastructure and bandwidth, and displayed in order to support proactive decisions by a distributed pool of subject matter experts. Recent projects involved power and fuel supply, energy management, mooring systems, thruster machinery, automated rig state detection, flow controls, and emission and regulatory reporting for NOx. The technology leverages advances in sensor size, deployment, resolution and frequency and limited global pools of subject matter experts to reduce operating costs.

CONCLUSION

The I-Platform solution applies best practices derived from numerous digital oilfield case studies to fixed surface equipment in order to reduce NPT. The aggregation of multiple datastreams from the platform, the use of predictive analytics and numerical analysis and the creation of an evolving historical database of trends and business rules all make this a solution unique to the offshore oilfield and ideally positioned to leverage current interest in optimizing operations. This solution is an end-to-end implementation for surface equipment that brings together mission-critical capabilities developed and already being deployed for downhole operations. It utilizes unique data analysis tools with artificial intelligence algorithms for codifying existing equipment expertise into business rules such as neural networks and self-organizing maps.

REFERENCES

Al-Khamis, M. N., Al-Hamzani, H. J., and Al-Adel, M. F., 2009. "Revamping Old Fields Using I-Field Technologies", SPE Paper #123540, 2009 SPE Annual Technical Conference and Exhibition, New Orleans, Louisiana, USA, 4-7 October 2009, Copyright 2009, Society of Petroleum Engineers, http://spe.org/atce/2009/pages/schedule/documents/spe1235401_000.pdf, accessed 1-Nov-2009

Athens Group, 2009. "The State of NPT on High Specification Offshore Rigs: First Annual Benchmarking Report", Whitepaper, http://www.athensgroup.com/docs/The_State_of_NPT_on_High_Specification_Offshore_Rigs.pdfDownloaded 22-June-2009

Benwell, T., 2010. "Can You Afford to Take the Risk?; The Case for Collaboration on Risk Mitigation for High-Specification Offshore Assets", Copyright Athens Group 2010, http://www.athensgroup.com/images/stories/articles/can-you-afford-risk.pdf, retrieved 12-Aug-2010.

Cramer, R., 2010. “Virtues of a virtual person monitoring all real aspects of all production facilities all of the time”, SPE Intelligent Energy Conference and Exhibition, 23-25 March 2010, Utrecht, The Netherlands, Paper Number 127513-MS, Copyright 2010. Society of Petroleum Engineers, DOI 10.2118/127513-MS

Dunham, C., 2009. “ESP ESP-Reliability Information and Failure Tracking System, Joint Industry Project, Overview”, C-FER Technologies, March 2009, http://www.esprifts.com/Slide%20Presentation.pdf, retrieved 6-April-2010

Farid, K., 2010. “SPE 2010 Digital Energy Workshop Literature Review”, http://communities.spe.org/TIGS/RTO/Shared%20Documents/Forms/AllItems.aspx?RootFolder=/TIGS/RTO/Shared%20Documents/Workshops, retrieved 12-Aug-2010.

Goodwin, S., Ford, A., Griffiths, P., Moore-Cernock, K., Williams, P., 2010. “Advanced Collaborative Environments – The Growth of a Capability Tranformation”, SPE Intelligent Energy Webinar, SPE Paper #128650, www.intelligentenergyevent.com/page.cfm/link=133, accessed 28-Sep-2010.

Heiberger, E., 2009. “The Wisdom of Maturity”. offshore-technology.com, SPG Media, 08-April-2009. Downloaded 22-June-2009. http://www.offshore-technology.com/features/feature52931/

Oberwinkler, C. and Stundner, M., 2005. “From Real-Time Data to Production Optimization”, SPE Production & Facilities 20 (3): 229-239. SPE-87008-PA, 10.2118/87008-PA

Perrons, R.K., 2010. “Perdido Ties Together Shell Digital Oilfield Technologies”, World Oil, vol. 231, no. 5, May 2010, www.worldoil.com/Perdido-ties-together-shell-digital-oilfield-technologies.html, Gulf Publishing Company, Houston, TX, USA.

Ramdial, A.M., Hudson, N. H., Pike, R. G., Rodriguez, J. C., Stratman, M. S., and Sama, S. S., 2009. “Model-Based Optimisation of a Gas Production System – The BP Trinidad Field Optimiser”, SPE Paper #124720, 2009 SPE Annual Technical Conference and Exhibition, New Orleans, Louisiana, USA, 4-7 October 2009, Copyright 2009, Society of Petroleum Engineers, http://spe.org/atce/2009/pages/schedule/documents/spe1247201_000.pdf, accessed 1-Nov-2009