

SPE 112150

Examples of Right-Time Decisions From High Frequency Data

J. Jane Shyeh, SPE, and Owen J. Hehmeyer, SPE, ExxonMobil Upstream Research Company; John M. Gibbeson, ExxonMobil Production, Esso Australia Pty. Ltd.; J. Jason Mullins, SPE, ExxonMobil Production–US Production Company; and Dickson Trujillo, SPE, ExxonMobil Production–Mobil North Sea LLC

Copyright 2008, Society of Petroleum Engineers

This paper was prepared for presentation at the 2008 SPE Intelligent Energy Conference and Exhibition held in Amsterdam, The Netherlands, 25–27 February 2008.

This paper was selected for presentation by an SPE program committee following review of information contained in an abstract submitted by the author(s). Contents of the paper have not been reviewed by the Society of Petroleum Engineers and are subject to correction by the author(s). The material does not necessarily reflect any position of the Society of Petroleum Engineers, its officers, or members. Electronic reproduction, distribution, or storage of any part of this paper without the written consent of the Society of Petroleum Engineers is prohibited. Permission to reproduce in print is restricted to an abstract of not more than 300 words; illustrations may not be copied. The abstract must contain conspicuous acknowledgment of SPE copyright.

Abstract

Asset performance can often be improved through continuous monitoring and/or through better utilization of information extracted from the high frequency data that are becoming more readily available in today's digital world. ExxonMobil has a long history of applying advanced technologies in asset management. Today, we continue to use new hardware, integrated software, and improved data infrastructure to enhance asset management workflows. ExxonMobil is taking an enterprise-wide approach (Reece et. al. 2008) to implementing digital technology in asset management.

This paper presents four examples where ExxonMobil has taken advantage of high frequency data for timely asset management decisions. These four examples represent implementation at four different operational scales: for reservoir management, for well management, for facility management, and for plant management. The four examples are: (1) For a West African reservoir: Permanent downhole pressure gauge data have added value in reservoir modeling that in turn provided a method for calculating reservoir rates; (2) For South Texas gas wells: Real-time data access and charting capabilities were implemented and advanced data analysis explored to identify well events and manage well work-over activities aided by artificial intelligence; (3) For Norwegian oil fields: An integrated facility model was developed and tuned for surveillance and operation of a network of wells and production facilities that are shared by multiple fields; (4) For an Australian production plant complex: Production from offshore platforms, a gas plant, a crude stabilization plant, a fractionation plant, and a tank farm was optimized with high frequency data and automatic process control.

Introduction

ExxonMobil has a long history of applying advanced technologies in asset management. As early as 1967, a CPC (Computerized Production Control) program was implemented in the company's US production assets. More recently, various ExxonMobil business units have implemented permanent monitoring (Chorneyko, 2006), automated artificial lift systems, and other digital technologies for efficiency improvement. Since 2000, the company has moved toward global standardization and best practices. The EM2010 (Reece et. al., 2005) program, which is currently in progress, has developed a business-driven vision and roadmap to a more integrated and automated subsurface work environment. Today, advances in digital technology are delivering many software, hardware, and infrastructure improvements that provide capabilities in remote real-time data access, right-time data analysis, right-time visualization, right-time optimization, and on-demand remote operability. The intersection of digital technology and asset management is an area that, if exploited, can improve operation and recovery. We believe these opportunities will increase as the use of digital technologies in asset management grows and as digital technology allows semi-automation of workflows.

The digital oil field has been a corporate strategic focus area since 2000 for many companies in the oil and gas industry. Major international oil companies have trademarked their approaches (e.g. Smart FieldsTM, FieldoftheFutureTM, and i-FieldsSM). ExxonMobil's approach to digital oilfields is to focus on the application of digital technologies to improve and enhance asset management workflows, fully leveraging our global functional organization and worldwide standardized asset management processes.

Four Example Applications of Digital Technology in Asset Management

Many projects have been justified by ExxonMobil operating companies to harness advances in digital technologies with the objective of improving asset management workflows and decisions. We have selected four examples implemented in the last five years to represent four different operational scales: for reservoir management, for well management, for facility management, and for plant management. We present these examples, beginning with the reservoir, moving through wells, the production facilities, and ending with a plant management system.

A Reservoir Management Example

The first example is for reservoirs in a major oil field in West Africa. Permanent downhole gauge pressures have been analyzed and information extracted to develop reservoir models. The models were then used to estimate contributing flow rates under a commingled production situation. We have demonstrated this method for several reservoirs in other regions (McCracken at.el. 2006) also.

Description of Application

In 2005, a three-zone gravel-packed oil well producing from an oil field in shallow water offshore West Africa was completed with 3 downhole pressure gauges and 3 downhole flow control valves. The intelligent completions were justified largely for the management of production commingled from three isolated formations/zones.

Good quality 10-minute interval downhole pressure data from each zone have been available since June 2005. The rate allocation plan was to conduct multi-point well tests for each zone monthly. In addition, the average reservoir pressures were estimated from high frequency flowing bottom-hole pressure data recorded by the permanent gauges for calculation of the zonal inflow from each reservoir (Brock et. al., 2006). Because of difficulties in mobilizing the test separator to the well-site, the well has not been tested monthly. There were also considerable uncertainties in the allocated rates because the commingled total flow rates were not directly measured at this well. Instead, the total well rate was back-allocated from the terminal to the platform, then to this well. Therefore, it was decided that an alternative method needed to be developed to supplement the current practice of rate estimation and allocation. To provide this alternative method for flow rate estimation, reservoir models were constructed and tuned using continuous downhole pressure gauge data.

Three single well models, one for each zone, were first developed to match the shut-in pressure transients and long-term pressure declines recorded by the permanent downhole gauges. We used pressure transient analysis (PTA) and rate transient analysis (RTA) commercial software for this task. Pressure build-ups recorded during shut-ins were screened and selected for the PTA. We relied heavily on the first multi-point well test conducted for this well when the flow control valve was shut-in downhole. **Figure 1** shows the reservoir model constructed for the upper zone that included several faults and a distant gas-cap. The pressure transient analysis results of the build-ups contained in the first 6 months of pressure gauge data are shown in **Figure 2**. The model parameters were tuned to match the pressure derivatives and to match the pressure decline measured for the first 11 months of production as shown in **Figure 3**. In Figure 3, the red-line represents the model results and the green symbols the pressure data. This model is then moved (dragged and dropped) into the companion RTA tool to calculate rates from pressures.

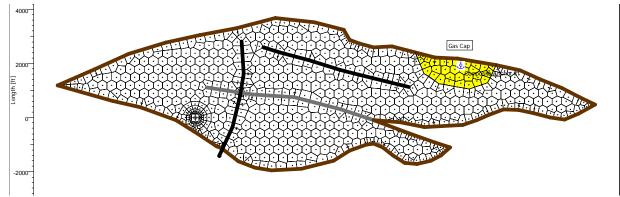
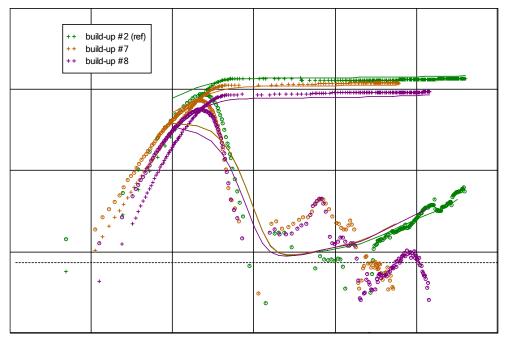
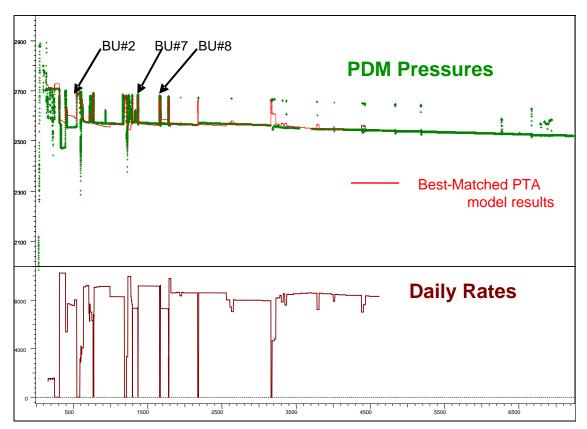


Figure 1 Upper Zone Reservoir Voronoi Model



Log-Log plot: dp and dp' normalized [psi] vs dt

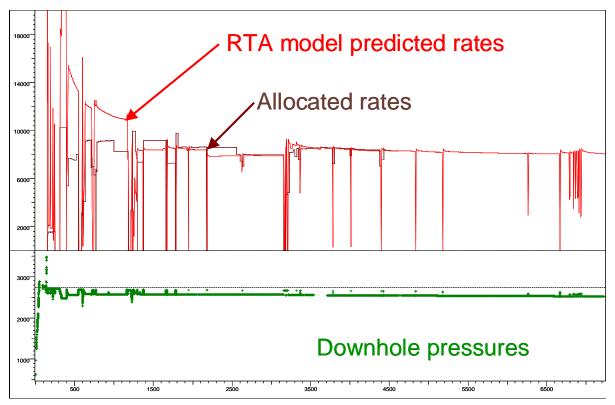
Figure 2 PTA Analysis of Unintentional Build-ups



History plot (Pressure [psia], Liquid Rate [STB/D]vs Time [hr])

Figure 3 Pressure History Match using the PTA Tool

As illustrated in **Figure 4**, this method provided more detailed rate estimates than the previous method. In Figure 4, the red-line represents the predicted rates from a model using the green pressure data as input. The red newly predicted rates are compared to the brown allocated rates estimated from the previous method. They compare well in later times (hours 1000 to 4000). During the first month (first 700 hours) of production, the well clean-up operations caused the pressures to be unstable leading to the disagreement between the rates calculated by the two methods. During the first month of production, we believe the previous method can provide a good estimate of rates because a multi-point well test was conducted during that month. Figures 1 through 4 are results for the upper reservoir zone only. Similar pressure-based modeling efforts had also been conducted for the middle and lower zones but are not shown.



Production history plot (Liquid Rate [STB/D], Pressure [psia] vs Time [hr])

Figure 4 Rates Calculated from High Frequency Pressures using the RTA Tool

We believe this West African field contains oil, gas, and water in each zone and hence multi-phase flow is expected later in the field life. After water or gas breakthrough, the PTA/RTA analysis and modeling described above will become invalid. Recognizing that, we also conducted an additional modeling study using our proprietary reservoir simulator EM^{power}. A detailed geologic model was not available at the time. The reservoir properties derived from the PTA analyses, including permeability-thickness and distance from well to boundaries, were honored in the construction of a relatively simple reservoir flow simulation model aimed at demonstrating the methodology appropriate for reservoir management later in field life. This reservoir simulation model included all three zones and allowed the examination of potential interactions among the three isolated zones connected at the well. A layer-cake type model of 22 layers with a slight dip was constructed. The key adjustable parameter was the fluid contact depth. This was justified because the available data have significant uncertainties. Very good pressure match was obtained and can be viewed in **Figure 5** for the first six months of production. The bestmatched model was then used to predict rates. The predicted rates are compared with previously allocated rates in **Figure 6**.

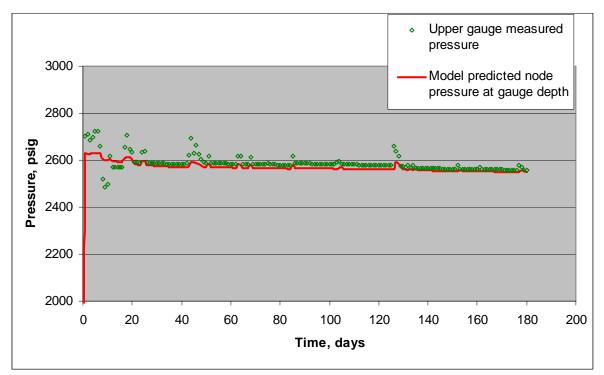


Figure 5 Pressure Match from Reservoir Simulation

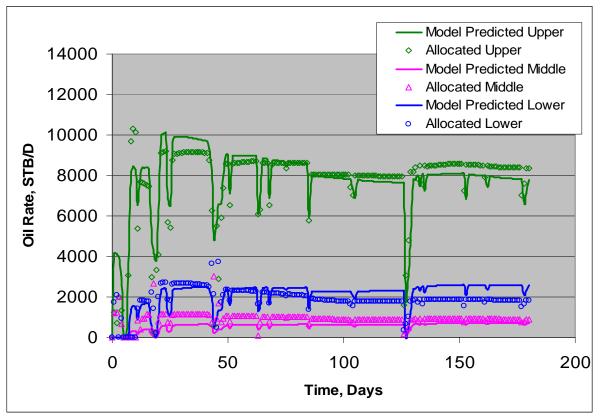


Figure 6 Comparison of Model Predicted to Allocated Rate

Business Impact

The allocation factors derived from the models discussed above, both from the simple PTA models and from the multiphase reservoir simulation model, are similar to those used to date by the business unit. However, the downhole pressure-based modeling methods provide alternatives and supplement the current method and may be relied on in the future

when production conditions change. Multi-phase rate allocation in commingled production is crucial for reservoir management decisions. We believe the pressure-based modeling can give more accurate rate allocation factors, particularly after breakthrough.

The ability to shut-in by zone using the downhole flow control and the availability of high frequency pressure data by zone from permanent gauges were both critical in providing reliable pressure buildup data needed for the modeling methods. In this example, the permanent downhole sensors and flow control valves were the enabling digital technologies that added value in the rate allocation workflow. In addition, it was also clear that the availability of high frequency downhole pressure data lessened the burden of frequent well testing and intervention that are costly and often rescheduled due to other well-site issues.

A Well Management Example

The second example is for a real-time data access and right-time data analysis application in South Texas. We first discuss a real-time data access project involving electronic flow meters for gas wells and the basic data charting tools developed for the project. Next we discuss how artificial intelligence (AI) based advanced data analysis tools aided in making right-time decisions based on real-time data.

Description of Application

Many of ExxonMobil's gas fields are instrumented with electronic flow meters (EFMs). A recent data access project has enabled surveillance engineers in Houston to remotely view hourly production flow rate, pressure, and temperature data in a S. Texas field on a daily basis. Workflows built around this improved data availability have allowed surveillance engineers to identify adverse well events and workover candidates. Adverse gas well events include liquid loading, well shut-ins, and gathering system upsets. Additionally, stimulation or remediation candidates are more easily identified by understanding features and trends within the real-time data. A sample of an automated chart showing gas well high-frequency data is shown in **Figure 7**. The cycling of rate (in red) suggests liquid loading of the well is taking place. If not dealt with in a timely fashion, build up of liquid in the wellbore can cause production stoppage. The temperature is shown in yellow, and the system pressure in black.

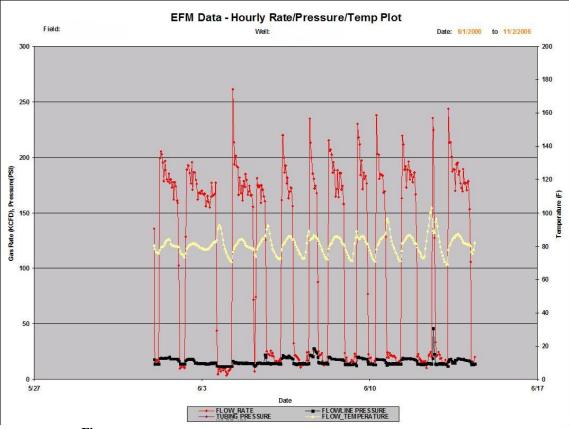


Figure 7 Sample high frequency data from a gas well undergoing liquid loading

It is desirable to automate the analysis of these data in order to rapidly identify and screen events for the surveillance engineer to review in more detail. Automation also allows for the institutionalization of engineering experience and judgment, enabling experienced engineers and technicians to do work that has historically been done by experienced surveillance engineers. We compare judgments made by experienced surveillance engineers to those made by a computer 1) via a full Bayesian Network and 2) via a complex logic tree.

Bayesian Networks (BNs) were constructed using a combination of statistical learning and expert knowledge. For each 24 hour block of time-series data, simple mathematical functions such as standard deviation, day over day change, and other measures were calculated for several variables. The BN probabilistically associated with each event a particular characteristic mathematical signature. A sample BN is shown in **Figure 8** with five variables for gas wells, including the standard deviation of the observed hourly rates recorded during the week prior to the last 24 hours, the number of times an hourly recorded rate of zero occurred during the week prior to the last 24 hours, the standard deviation of the observed hourly rates recorded during the number of times an hourly recorded rate of zero occurred during the number of times an hourly recorded rate of zero occurred during the last 24 hour period, the number of times an hourly recorded rate of zero occurred during the last 24 hour period, the number of times an hourly recorded rate of zero occurred during the last 24 hour period, and the change in the absolute value of the rate during the last 24 hours normalized by the average rate. Each of the five rate-derived variables was a node in the network. Each node contained the probabilities of the value of that variable falling into certain ranges.

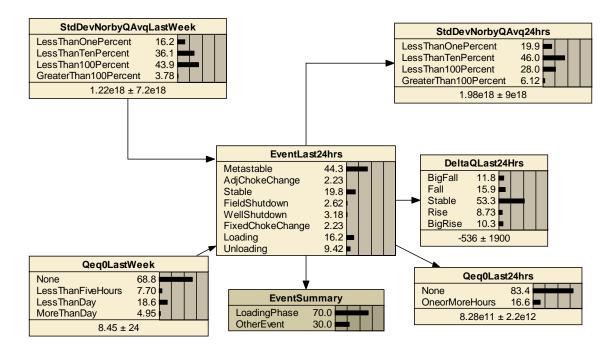


Figure 8 A simplified example of a BN for a gas field

Testing using three fields in South Texas showed that the BN-based method was able to recognize events with a 75-90% success rate depending on the well and field, although the statistical learning process had to be completed separately for each field. The BN-based method showed a good balance between a high detection rate and a low number of false alarms. While the BN-based method successfully recognized events, it was unable to predict events given the available data.

Not all of the variables contained in the BN were equally important for the recognition of events. Testing using the BN led to the discovery of which variables contributed most strongly, and subsequently a logic tree was built using the three most important variables as shown in **Figure 9**. Threshold values for these three key variables were set to determine the most likely event. We found the overall detection rate using the logic tree approach was about 10 percentage points lower than that of the BN-based method. In contrast to the BN-based method, which is probabilistic and assigns a statistical confidence to each recognized event, the traditional method makes its best estimate for the recognized event without any associated statistical confidence.

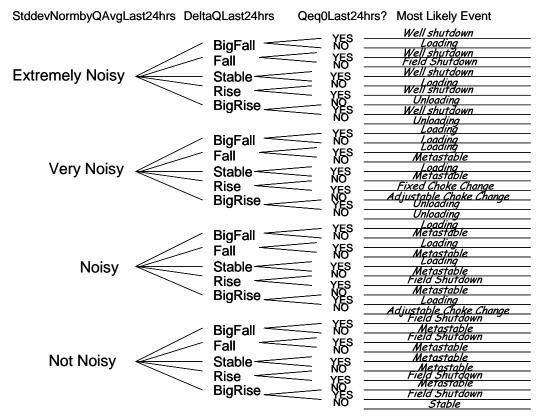


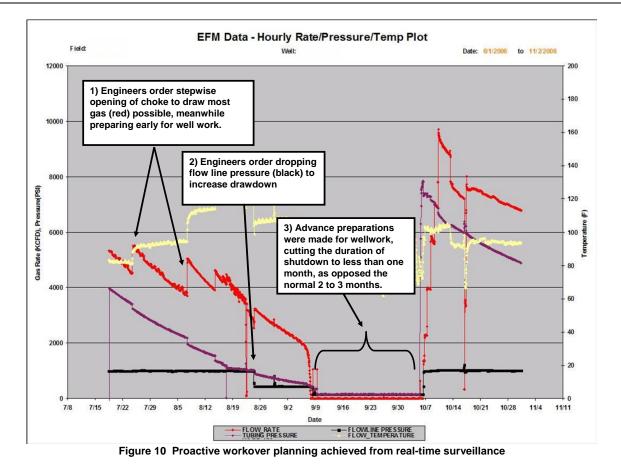
Figure 9 The logic tree approach

Real-time (and/or right-time) data access is a necessary underlying component of a state-of-the-art surveillance program. However, the level of mathematical complexity and analysis automation that is economically appropriate varies by asset. More advanced methods of analysis using BNs or logic trees, while requiring more effort to set-up than a single-value threshold method, could institutionalize experience needed to drive production stewardship to the next level of performance. ExxonMobil's Production Surveillance and Optimization effort (Crawford et.al., 2008) and other efforts like US Production's EFM are laying the digital foundation for powerful and flexible surveillance solutions.

Business Impact

The impact of real-time EFM data on ExxonMobil's US production to date has been primarily through the increased analysis that can be performed for adverse event recognition and optimization. Workovers have been identified and completed as much as two months sooner than with traditional data and methods, as demonstrated in **Figure 10**. In Figure 10, production rate is shown in red, temperature in yellow, tubing head pressure in purple, and system pressure in black.

Production has also been increased through optimization driven by the active monitoring allowed by real-time data. Chokes are more aggressively managed allowing for optimum production. Automated processes such as reporting of standard, calculated, thresholded parameters have enabled active surveillance of a larger number of wells per engineer.



Most Probable Well Status [Time and Date]				
Well 1	loading	32.7%	-178.5%	
Wel 2	metastable	5.4%	-11.4%	
Well 3	loading	16.8%	-51.9%	
Well 4	metastable	11.5%	-29.4%	
Wel 5	metastable	16.1%	-27.6%	
Well 6	metastable	5.4%	-6.8%	
Well 7	null (likely shutdown)			
Well 8	metastable	3.8%	-4.2%	
Wel 9	adj choke change	11.1%	15.5%	
Well 10	loading	18.3%	-42.4%	
Well 11	metastable	0.9%	-2.7%	
Well 12	null (likely shutdown)			
Wel 13	metastable	1.9%	-5.6%	
Wei 14	metastable	2.9%	-1.2%	
Well 15	metastable	0.1%	-0.1%	
Well 16	metastable	3.3%	-9.8%	
Well 17	null (likely shutdown)			
Well 18	null (likely shutdown)			
Well 19	metastable	0.4%	-0.1%	
Well 20	metastable	3.4%	4.2%	
Wel 21	null (likely shutdown)			
Well 22	null (likely shutdown)		0.0%	
Well 23	null (likely shutdown)		0.0%	
Wei 24	null (likely shutdown)			
Wel 25	metastable	2.3%	9.3%	

Figure 11 Sample prioritized well status display

Traditionally, surveillance engineers look at charts of flow rate vs.time for wells with production drops in an effort to determine the cause(s). With an automated analysis method such as a BN or BN-derived logic block, the surveillance

engineer can use a diplay like that shown in **Figure 11** to prioritize which wells to examine in more detail, skipping the wells for which the determined event is known not to be detrimental.

A Facility Management Example

The third example is a case in which operational workflows for wells and surface production facilities in the North Sea have been enhanced resulting in asset performance improvements. This was achieved through real-time data access and right-time data trending, analysis, integrated modeling, and optimization.

Description of Application

In ExxonMobil North Sea Production, wells in many fields of the Norwegian sector are instrumented with sensors and real-time data are acquired and stored in a commercial real-time data system. Production facilities are shared among three fields: Balder, Ringhorne, and Jotun (BRJ). The BRJ facilities are fully connected via pipelines for fluid transfer from one platform to another as depicted in **Figure 12**. Crude oil pipelines are used from Ringhorne to Balder and Jotun; and gas pipelines are used from Balder to Jotun. There are lines from Balder that supply gas for lifting wells at Jotun and Ringhorne. Sharing of facilities creates constraints and opportunities for optimization.

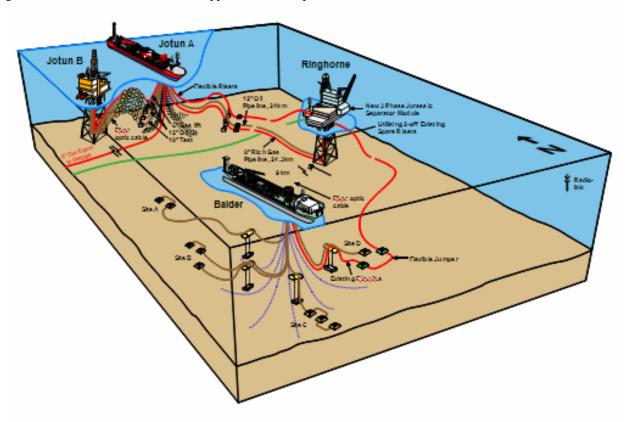


Figure 12 Balder Ringhorne Jotun Production Facility SchematicDiagram

An integrated production model was developed and is being used for routine and non-routine asset management decisions. Using commercial real-time system software, a display that mimics the integrated production model layout was created to view process variables for both surveillance and facilities engineers. With this implementation, it is relatively easy to correlate high frequency data with variables in the integrated production model. The high frequency data used in the model include bottom-hole pressure, bottom-hole temperature, wellhead pressure, wellhead choke opening, lift-gas injection rate, total fluid rates between the platforms, flares, gas pressure, cumulative production, compressor vibration, and tank levels. These variables are available real-time for all the wells and in all stages of the production process. A typical display is shown on the left of **Figure 13** and compared side-by-side to the integrated production model on the right.

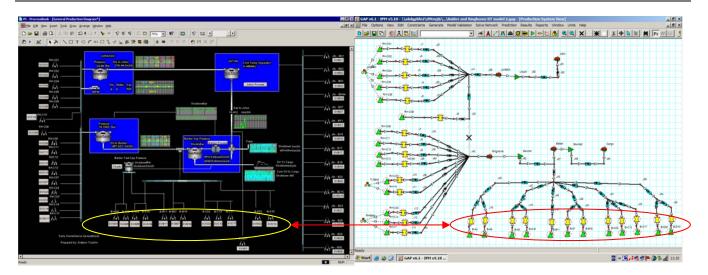


Figure 13 Real-time system display (left) and the integrated production model layout (right) for BRJ

This implementation of real-time capabilities for viewing and charting data has been very useful to engineers in the office and has become an aide in communicating to well-site operators. These visualization capabilities are used for daily review of key well data, event recognition and associated downtime planning, optimization of gas injection and lift-gas distribution, surveillance by deviation, and identification of well slugging. Right-time decisions are made based on data less than one day old. The daily decision is then quickly communicated to the offshore operators. The response to well setting changes is also monitored real-time for the well and for the total system. At present, real-time data viewing and charting capabilities are available only to a few operators, but are being rolled out to Norwegian platforms one by one for operators' use. This is so the operators can view the same display as the engineer, making communication easier. The operators can also use these capabilities to handle platform issues such as flare limits and compressor vibration, and monitor production well tests and valve integrity tests.

The integrated production model is tuned with high frequency production data and with periodic test data. This model is run almost daily to obtain recommended gas injection rates and other settings, and to prepare the offshore production plan. The model enables optimization of decisions and recommendations. Once the settings are changed by offshore personnel, the well and system responses are monitored and evaluated real-time by comparing to model predictions. The model takes into account system constraints, including maximum gas injection rate and maximum liquid rate at the separator. When measured data deviate significantly from model predictions of total field rates, the parameters (e.g. solution GOR, lift gas rate, watercut, and etc) for each well are updated and the model is run again till the discrepancy is resolved. The model also enables estimation of associated downtime for any event requiring well shut-down.

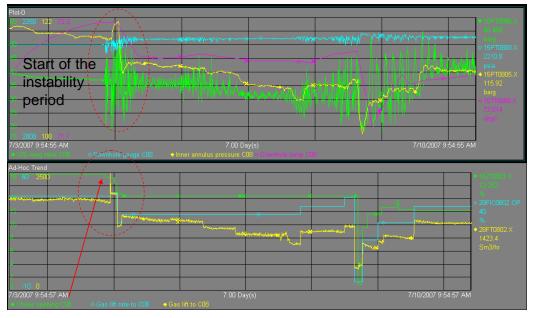


Figure 14 Real-time well slugging recognition

When the recommended gas lift injection does not produce the expected well rate, and measurements are not faulty, it may be an indication of well slugging. As shown in **Figure 14**, this well was stable until the gas-lift choke was adjusted by the operator after a crew shift. The well began to slug severely (evidenced by the green trace in the red circle of the upper chart). Gas lift and well chokes were then adjusted to bring back the stability.

Business Impact

Tangible and intangible benefits have been observed from the implementation of real-time data visualization and modeling in Norway. Some are listed below:

- The greatest benefit is in the reduced time required for daily surveillance activities
- The time lag for decisions has been reduced.
- Surveillance engineers can now spend 60% of their time on optimization and finding new opportunities instead of half of their time on gathering and organizing data.
- 10% reduction in lift gas consumption for the same volume of production has been estimated in some cases.
- Close monitoring has led to general improvement in well deliverability.
- The typical time required to bring well slugging under control has been reduced from seven days to three days.

A Plant Management Example

The fourth example shows how the operations of an Australian petroleum processing complex were optimized using a realtime surveillance program implemented in phases beginning in 2002. The program included both real-time monitoring and automatic process control.

Description of Application

Esso Australia operates several offshore production platforms in Bass Strait, a crude stabilization and gas processing plant at Longford, and an LPG fractionation plant at Long Island Point as part of their Gippsland operations (**Figure 15**). The Technical Surveillance Program (TSP) has been implemented at both the operator level and engineer level since 2002 for the Gippsland operations (Gibbeson, 2003). A real-time data acquisition system has been in place for over eight years in the region. Both surface and subsurface data are available to engineers remotely in Melboure. This Technical Surveillance Program for the Gippsland operations was enabled by leveraging existing process control and process information systems and through development of more structured engineering monitoring system. The objectives of the program include: maintaining the process within safe operating limits, targeting optimal performance, identifying equipment and system performance deviations, and continuous improvement.

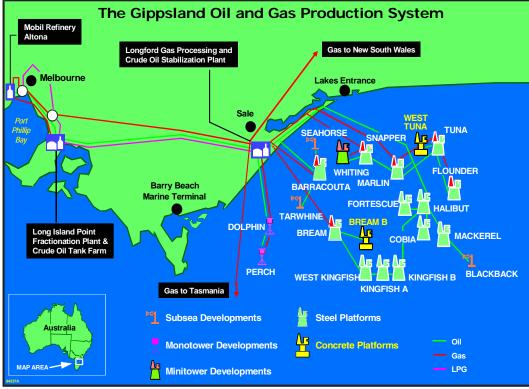


Figure 15 The Gippsland Oil and Gas Production System

At the operator's level, the process is monitored continuously and assisted by process alarms to maintain the plant within the desirable operating zone. Safe operating limits define the outside boundary of the operating envelope which is secured with automatic shut-down and other protective devices. Alarm and limit conditions associated with these parameters have been incorporated into the operations control system and pre-defined operator response options appear automatically on the screen if the conditions are reached.

At the engineer's level, the TSP is a systematic periodic monitoring process focusing on optimum performance and continuous improvement. It is structured using elements of a company standard operations integrity management system. Within this framework, engineering spreadsheets have been developed with direct links to process data via a commercial real-time system software. The spreadsheets enable plant engineers to efficiently monitor the key performance indicators, pre-define the acceptable operating range, calculate statistical performance index, highlight deviations, and hyperlink back to the real-time system for more detailed trouble shooting. Day to day deviations and performance improvements are reviewed at the working level. More significant issues are formally investigated and reviewed with management. Key data and overall performance are summarized monthly and formally reviewed. A schematic of the engineering surveillance process is shown in Figure 16.

Structuring the TSP under a company standard management system has been the key element in ensuring the program is effective and continues to function. It also provides the means to transfer this implementation experience to other assets at a different scale.

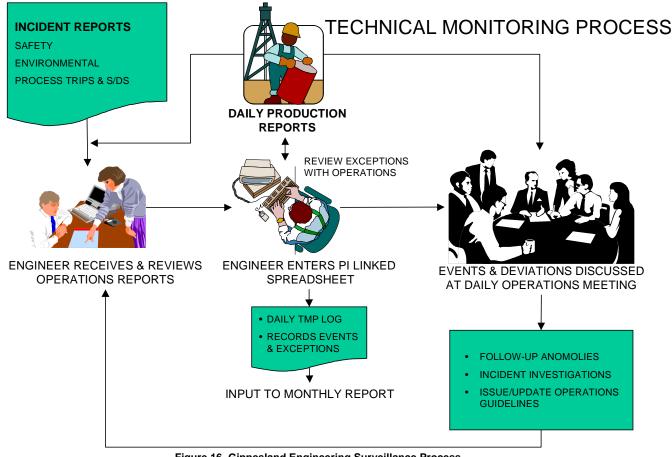


Figure 16 Gippesland Engineering Surveillance Process

Business Impact

Significant benefits were observed in the Gippland operations after the implementation of the Technical Surveillance Program. Tangible benefits were registered in integrity, product quality, recovery, efficiency, reliability, and capacity.

- Integrity significant reduction in the number of process excursions (i.e. fewer alarms) were registered
- _ Quality – fewer product quality excursions (i.e. in crude oil, LPG, natural gas products) were recorded
- Recovery maximized NGL recovery. Protocols were developed for plant operation for maximum NGL recovery. The benefit quantified for peak recoveries has outweighed the cost.

- Efficiency and Reliability bad actor equipment such as system bottlenecks and poorly performing control systems are quickly identified and occurance frequency quantified.
- Capacity allows operations near seasonal constraints

Less tangible benefits include:

- Faster response to operational issues
- Increased confidence that personnel will follow-up on deviations
- Closer cooperation between engineers and operators
- Better judgement by operators as they gain system-wide understanding

There is a significant ongoing deployment of engineering resources to drive, support, and maintain the system. However, the TSP is considered cost effective because it has focused engineering effort and improved process surveillance efficiencies. The system continues to evolve through ongoing refinements.

Summary and Conclusions

ExxonMobil has implemented digital technologies to improve asset management workflows, as needs arose and when the value was clear. The implementations have been on various levels and have resulted in improved management of reservoirs, wells, facilities, and plants. Our observations and conclusions from the examples selected for this paper include:

- 1. Data that have been automatically acquired and organized for specific workflows and made readily available to engineers and operators can improve their efficiency and effectivness.
- 2. Integration of real-time high frequency data can deliver desirable data redundancy -- extracted information can validate models and other measurements and improve understanding or increase confidence.
- 3. Higher frequency data make troubleshooting easier, ensuring problems will be addressed in a timely manner.
- 4. Close monitoring and trending of high frequency data often provides unexpected benefits via relaxation or removal of system constraints.
- 5. Sharing of data trends benefits engineers and operators and enables collaborations between them.
- 6. The level of the appropriate mathematical complexity for data analysis automation varies by asset. For example, more advanced analysis methods harnessing AI advances may require more effort to set-up than a single-value threshold method.
- 7. Artificial intelligence could provide a means to institutionalize experience and expertise needed to drive production stewardship to the next level of performance.
- 8. Fit for purpose, easy to use tools and methods are needed to extract valuable information contained in large volume, high frequency data.

References

- Brock, W. R., Oleh, E. O., Linscott, J. P. and Agara, S., "Application of Intelligent-Completion Technology in a Triple-Zone Gravel Packed Commingled Producer", SPE101021, presented at the 2006 SPE Annual Technical Conference and Exhibition held in San Antonio, Texas, 24-27 September 2006.
- Chorneyko, D. M., "Real-time Reservoir Surveillance Utilizing Permanent Downhole Pressures An Operator's Experience", SPE 103213, presented at at the 2006 SPE Annual Technical Conference and Exhibition held in San Antonio, Texas, 24-27 September 2006.
- 3. Crawford, M. L., Hoefner, M. L., and Oakes, J. E., "A Standard Solution for Upstream Oil and Gas Surveillance", SPE 112152, 2008 IE Conference in Amsterdam
- 4. Gibbeson, J. M., "Petroleum Processing Plants Technical Surveillance Program", APPEA Journal 2003
- 5. McCracken, M. E. and Chorneyko D. M., "Rate Allocation Using Permanent Downhole Pressures", SPE 103222, presented at the 2006 SPE Annual Technical Conference and Exhibition held in San Antonio, Texas, 24-27 September 2006.
- 6. Reece, C. A., Catron, R. E., Hammond, R. D., and Schmidtke E. A., "Optimizing the Subsurface Work Environment of the Future". SPE 96944, presented at the 2005 SPE Annual Technical Conference and Exhibition held in Dallas, 9-12 October 2005.
- 7. Reece, C. A., Hoefner M. L., and Seetharam R.V., and Killian, K.E., "Enterprise-Wide Approach to Implementing Digital Oil Field", SPE 112151, 2008 IE Conference in Amsterdam