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Drilling for Deepwater Data: A Forensic Analysis of the Gulf of Mexico Deepwater Horizon Disaster

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ABSTRACT

During the cementing and pumps-off phase of oil drilling, drilling operations need to know, in real time, about any loss of hydrostatic or mechanical well integrity. This phase involves not only big data but also high-velocity data. Today's state-of-the-art drilling rigs have tens of thousands of sensors. These sensors and their data output must be correlated and analyzed in real time. This paper shows you how to leverage SAS® Asset Performance Analytics and SAS® Enterprise Miner™ to build a model for drilling and well control anomalies, to fingerprint key well control measures of the transient fluid properties, and to operationalize these analytics on the drilling assets with SAS® Event Stream Processing. We cover the implementation and results from the Deepwater Horizon case study, demonstrating how SAS analytics enables the rapid differentiation between safe and unsafe modes of operation.

INTRODUCTION

On April 20, 2010, the Deepwater Horizon was located 28° 44′ 12.01″ N, 88° 23′ 13.78″ W in the Mississippi Canyon, Block 252 of the U.S. Outer Continental Shelf, Gulf of Mexico. The Deepwater Horizon mobile offshore drilling unit (MODU) was attempting to temporarily abandon the Macondo well (OCS-G 32306 001 ST00BP01). The well was currently drilled to a depth of 18,360 vertical feet. The temperature was approximately 69 degrees that day, winds were at approximately 6 knots, and the seas were at less than 1 foot. There were 126 personnel on board. At approximately 21:50 hours, a large explosion ripped through the Deepwater Horizon, eventually killing 11 personnel, injuring 16 others, sinking the Deepwater Horizon, and initiating the largest oil spill in U.S. history and the subsequent massive environmental catastrophe. This paper does not attempt to rehash a root cause analysis of the accident, but rather it seeks to analyze the data that survived the accident and to demonstrate the use of statistics, analytics, and SAS technologies that could have helped advise the crew of the Deepwater Horizon and potentially prevented this incident. In this paper, we analyze two of the anomalies from the Deepwater Horizon, identify how you might detect those anomalies using SAS solutions, and describe how you might operationalize a model for such detection.

INFORMING FIRST PRINCIPLES

This paper advocates for a data-driven methodology that informs physics and first principles. It is the authors' contention that scientific empirical limits such as lithostatic models of overburden gradient and hydrostatic models of pore pressure, two critically important measures in deepwater drilling, can be augmented by data-driven algorithms. The automatic identification of anomalies in measurements like stand pipe pressure, fluid density, and flow rates, coupled with machine learning modules like (equipment) survival analysis, enables the data-driven approach to predict when either the lithostatic or hydrostatic failure points will be reached, which can lead to a catastrophic failure. This fundamentally changes control of the drilling process. Rather than monitoring for influx, and then reactively managing the risk, the driller is now able to proactively manage the risk, comfortable in the knowledge that the system will also automatically identify anomalies that might indicate a potential well integrity failure.

DEEPWATER HORIZON DATA

The data in this use case was compiled from several public sources. Despite real-time drilling data from the Deepwater Horizon being managed by two systems, a HiTec system deployed by NOV and a Sperry Drilling Services system deployed by Halliburton, only the data from the Sperry Drilling Services system survived the explosion. The Sperry Drilling Services data during those critical moments onboard is shown in Figure 1.

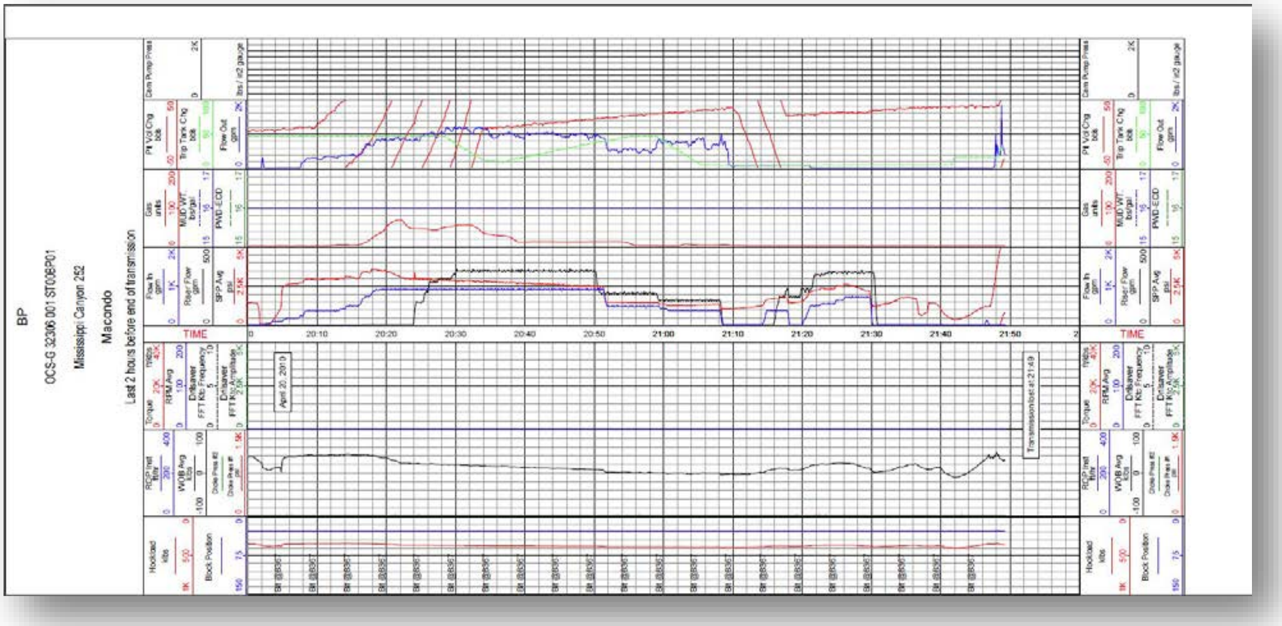


Figure 1: Real-time Data from the Deepwater Horizon

In this paper, we incorporate data from five measures:

1. Stand Pipe Pressure
2. Kill Pipe Pressure
3. Flow In
4. Flow Out
5. Riser Flow

SIGNIFICANT ANOMALIES IN THIS USE CASE

There were, of course, a multitude of issues that had an impact on the catastrophe that unfolded on April 20, 2010. In this paper, we chose to focus on two of those key elements: first, the failure by human operators to identify an influx of reservoir hydrocarbons into the annulus prior to the cementing operation; and second, the failure to correctly identify that the wellbore integrity negative pressure test was unsuccessful. Our examination focuses on two of the key anomalies that related to both of these situations:

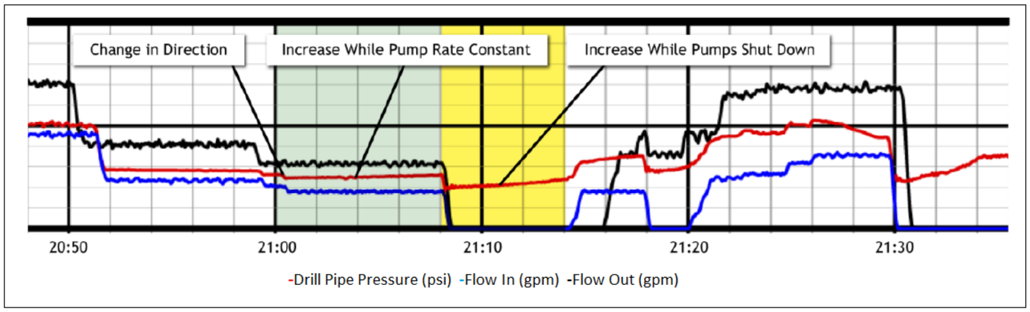
1. Stand pipe pressure increase with pump rate either constant or off
2. Inadequate decline of flow out with pump rate either constant or off

SEQUENCE OF EVENTS

From Figure 3, we can almost see with the human eye that between 9:01 pm and 9:08 pm, the drill pipe pressure increased by approximately 100 psi with a constant flow in. At 9:08 pm, the pumps are switched off and flow in is reduced to 0. Initially, the flow out signature drops but rapidly increases again through 9:14 pm. Either of these patterns are enough to red-flag the operation that additional flow is in the annulus and is almost certainly coming from the formation as the well is kicking.

Although we did not include it in this analysis, the authors also noted from drilling activity reports that seawater was displacing drilling mud inside the casing during this time. The hydrostatic effect of a less dense fluid should have resulted in a decreasing stand pipe pressure. This is a good example of where contextual analytics can also be used to enhance operational oversight.

It is always easier to identify failure patterns after the event. However, in the heat of the moment on a busy drill floor, where operators are focused on the safety of employees and the efficiency of the operation while theyare being distracted by noisy phone calls, it is easy to miss the obvious. The signal patterns exhibited in Figure 2 were a strong indication that the well was experiencing a kick (an unwanted influx of fluids or gas into the wellbore, which could result in a blowout). Either of these patterns could and should have flagged the drill crew to begin well control measures. However, when you look at the reality of the operational view that a driller has, shown in Figure 3, it is easy to see how this could be missed.



Sperry-Sun data/TrialGraphix

Figure 2: Drill Pipe Pressure Anomalies

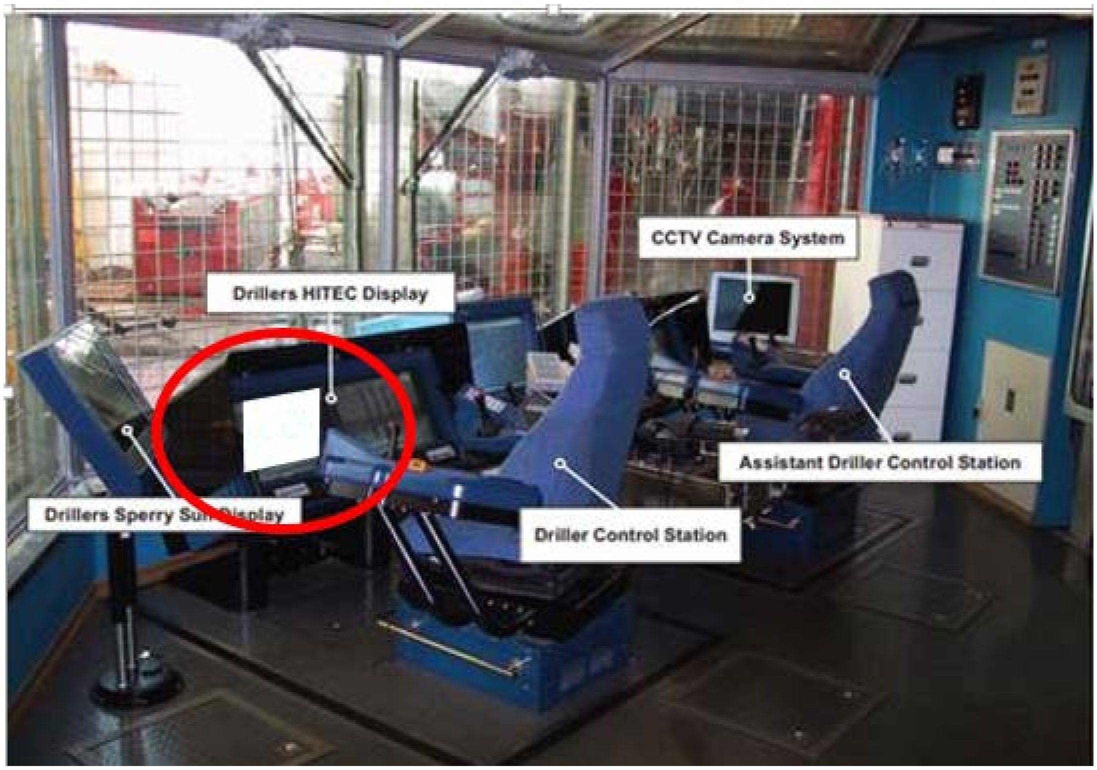


Figure 3: Driller's View on the Deepwater Horizon

ABNORMAL FLOW-OUT SIGNATURE

At approximately 9:08 pm, when the top of the spacer column from the ongoing cement job reached the surface, the crew shut down the pumps. As shown in Figure 4, for about a minute after this event, the flow-out spiked beyond the Deepwater Horizon's typical flow-out signature. With pumps off, flow-out continued when it should have settled to 0. Again, the identification of the anomaly was placed into the hands of the human operator at a time when there was chaos and confusion.

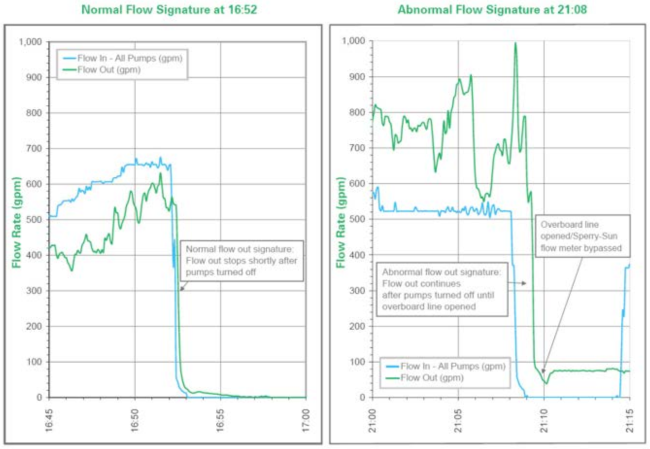
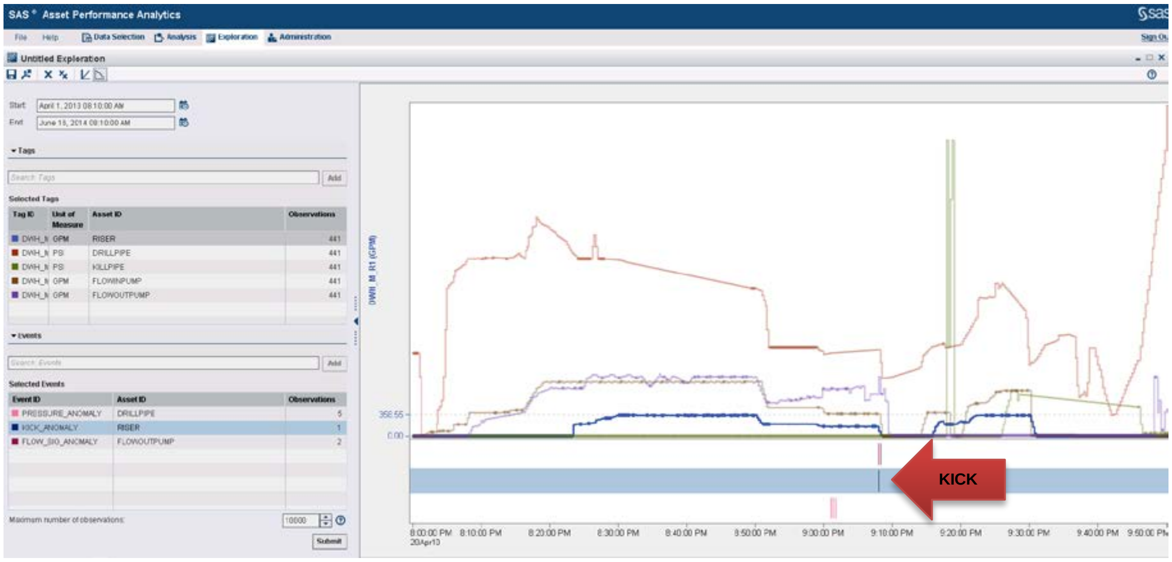


Figure 4. Abnormal Flow Signature

USING SAS ASSET PERFORMANCE ANALYTICS TO IDENTIFY ANOMALIES

In SAS Asset Performance Analytics, sensor data can be visually explored and further analyzed with various techniques like Pareto analysis, Correlation analysis, and Root Cause analysis. The exploration capability in SAS Asset Performance Analytics allows you to visually tie sensor data and events together in the same visualization. Figure 5 shows the five Deepwater Horizon sensors and the correlated “Kick”, “Flow Signature”, and “(Drill Pipe) Pressure” events (anomalies) integrated in the exploration tab, with the “Kick” event highlighted.



Start: April 1, 2013 08:10:00 AM

End: June 18, 2014 08:10:00 AM

Selected Tags

Tag ID	Unit of Measure	Asset ID	Observations
DWH_M	GPM	RISER	441
DWH_M	PSI	DRILLPIPE	441
DWH_M	PSI	KILLPIPE	441
DWH_M	GPM	FLOWINPUMP	441
DWH_M	GPM	FLOWOUTPUMP	441

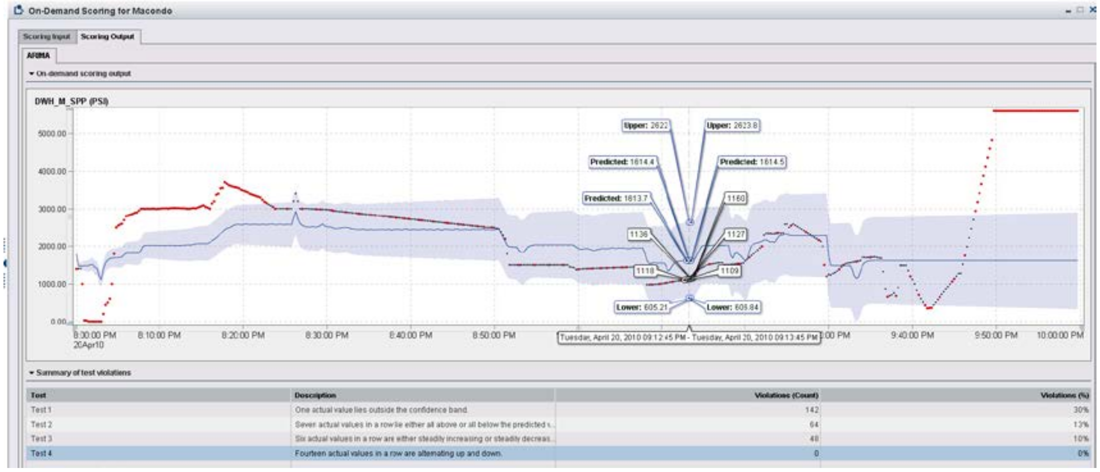
Selected Events

Event ID	Asset ID	Observations
PRESSURE_ANOMALY	DRILLPIPE	5
KICK_ANOMALY	RISER	1
FLOW_SIG_ANOMALY	FLOWOUTPUMP	2

Maximum number of observations: 10000

Figure 5. SAS Asset Performance Analytics Event Exploration

Also in SAS Asset Performance Analytics, you can perform stability monitoring within the Analysis/Analytical Workbench function. The software’s Stability Monitoring Model is an end-to-end predictive modeling tool that allows the user to predict how sensors should behave during stable operation. Using this tool, you can identify unstable operation with the goal of identifying problems before they become a major issue. SAS Asset Performance Analytics supports linear regression and ARIMA models within the stability monitoring feature. Figure 6 shows the last two hours of the Deepwater Horizon data and the related “violations” using an ARIMA model.



Test	Description	Violations (Count)	Violations (%)
Test 1	One actual value lies outside the confidence band.	142	30%
Test 2	Seven actual values in a row lie either all above or all below the predicted v...	64	13%
Test 3	Six actual values in a row are either steadily increasing or steadily decreas...	48	10%
Test 4	Fourteen actual values in a row are alternating up and down.	0	0%

Figure 6. SAS Asset Performance Analytics Stability Monitoring

SAS ENTERPRISE MINER

SAS Asset Performance Analytics includes the SAS® Enterprise Guide® and SAS Enterprise Miner solutions. SAS Enterprise Guide and SAS Enterprise Miner allow you to customize and enhance SAS Asset Performance Analytics by developing new models and analytical tools. SAS Asset Performance Analytics models can be enhanced by launching a SAS Asset Performance Analytics data set in SAS Enterprise Guide, SAS Enterprise Miner, or both. SAS Enterprise Miner provides state-of-the-art predictive analytics and data mining capabilities that enable you to analyze complex data, find useful insights, and act confidently to make fact-based decisions. SAS Enterprise Miner helps you build a model that predicts asset failures, reduces unnecessary maintenance, and increases uptime to optimize asset performance. As shown in Figure 4, we can build a model that helps us detect flow anomalies. SAS Enterprise Miner (see Figure 7) shows a graphical representation of our model, which incorporates the Time Series Similarity node, the Decision Tree node, the Neural Network node, and the Regression Node. SAS Enterprise Miner automatically compares models, selects the best performing model, and then scores the results. Model logic can then be exported in various forms, including Java code, C code, and other SAS programs.

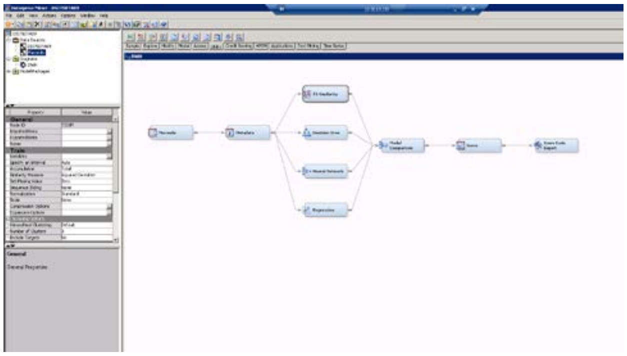
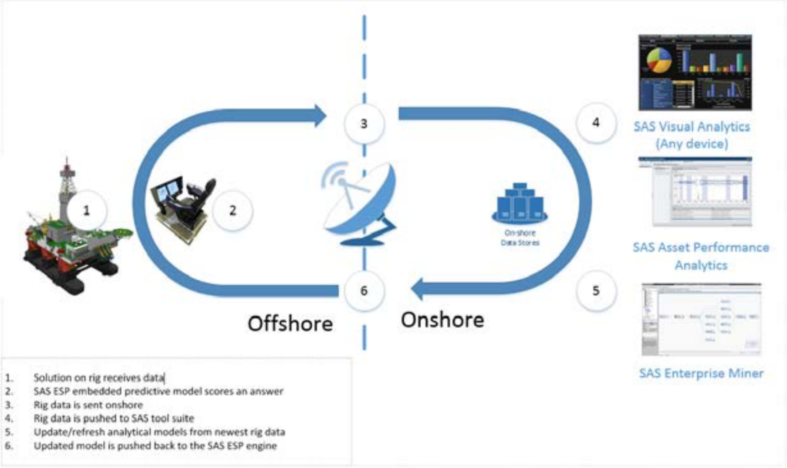


Figure 7. SAS Enterprise Miner Deepwater Horizon Abnormal Flow Model

SAS EVENT STREAM PROCESSING ENGINE

Once a model is found to be reliable and useful, it can be integrated with SAS Event Stream Processing and operationalized as physically close to the asset as necessary. SAS Event Stream Processing enables you to continuously analyze events as they occur so that you can take real-time, analytically sound actions. SAS Event Stream Processing, which can handle hundreds of thousands of model scoring transactions per second, is a lightweight, platform-independent engine, allowing it to be deployed offshore, onshore, and virtually anywhere. Figure 8 shows an analytical lifecycle for a rig-based solution.



1. Solution on rig receives data
2. SAS ESP embedded predictive model scores an answer
3. Rig data is sent onshore
4. Rig data is pushed to SAS tool suite
5. Update/refresh analytical models from newest rig data
6. Updated model is pushed back to the SAS ESP engine

Figure 8. Analytical Lifecycle

CONCLUSION

This paper demonstrates how to use SAS technologies to apply a data-driven approach to inform physics first principles in the drilling phase of oil production and how to operationalize SAS analytics in a real-world production environment. SAS technologies can help identify anomalies, predict failure, and ensure a safe workplace. These SAS technologies can be operationalized in many ways, including with SAS Event Stream Processing, which can handle hundreds of thousands of calculations per second. The application of this approach and these technologies can automate the recognition of risk patterns in operational data and then, as shown in Figure 9, present the results in a format that makes it easier for the operator to consume during critical operations.

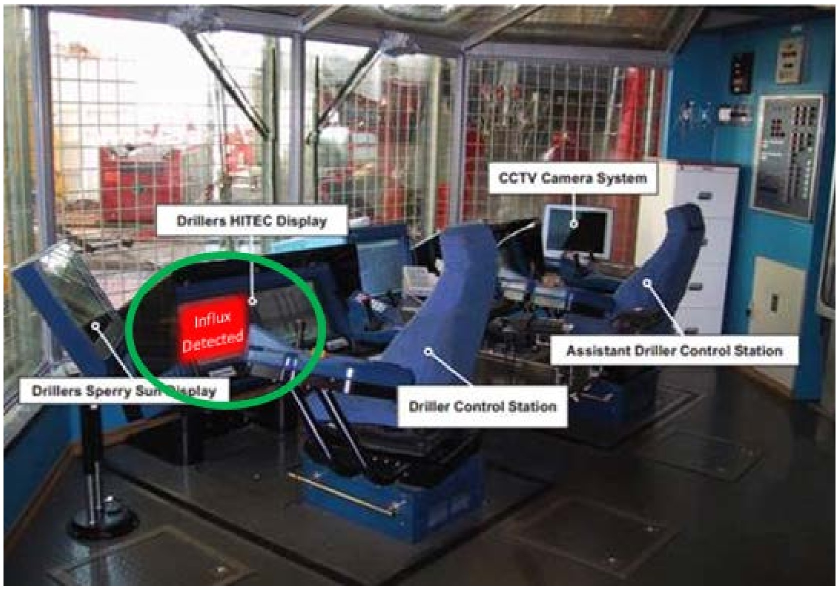


Figure 9. Clear Advice Enabled by SAS Asset Performance Analytics and SAS Event Stream Procssing

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Chief Counsel's Report on Deepwater Horizon Oil Spill. http://www.eoearth.org/files/164401_164500/164423/full.pdf

ACKNOWLEDGMENTS

RECOMMENDED READING

- *Harness Oil and Gas Big Data with Analytics: Optimize Exploration and Production with Data Driven Models,* Keith Holdaway, Wiley Press, 2014.

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