AADE-19-NTCE-011

Algorithm Automates Early Event Detection Leading to Reduced Drilling Risk and NPT

Lawrence Herskowitz, Halliburton

Abstract

Drilling optimization technicians strive to increase the efficiency of the drilling operation; however, unforeseen events can occur that negatively impact this efficiency. While drilling a well, it is critical to maintain a vigilant watch for various events that could require intervention. Negative results from undetected events include an increase in non-productive time (NPT), loss of valuable fluids, wellbore collapse, or even loss of well control. Each event has its own indicative multidimensional measurement profile. An expert technician monitors various sensors for these profiles to identify events and take corrective actions before drilling is negatively affected. This process requires focus and a breadth of drilling knowledge. Although these expert technicians are valuable, they are often limited in the number of wells they can effectively monitor simultaneously. An algorithm to automate this process has been developed to address this and thereby increase efficiency.

A survey of representative profiles from expert technicians was used to develop rules for these events. Using a combination of custom simulations and advanced statistics, the algorithm can detect current drilling conditions in real time and determine whether or not an event is likely to occur or is currently occurring. The algorithm gives a score to indicate the severity status of the event to the technician. This method of early event detection can reduce risk and NPT during drilling operations. Using these early detection systems enables real-time fluid engineers to efficiently monitor many more drilling operations than was previously possible.

Introduction

While drilling, it is important to monitor for negative events that threaten the well, such as pack off, bit balling, and poor hole cleaning. Failure to monitor these events can lead to prolonged down time or even to loss of the well.[1-4] Sensors and manual tests are used to measure characteristics of the well and drilling fluid. Originally, various personnel monitored individual measurements for anomalies. However, because the information that they received was segregated by their specific job roles, their effectiveness and efficiency was limited.[5]

An applied fluids optimization (AFO) monitoring service has been developed to improve this shortcoming. This service provides AFO engineers who are trained to monitor and interpret data from various disciplines. They receive the data from sensors and manual tests, as well as from a drilling fluids modelling software program that can predict well characteristics.[6] For example, the program can model the expected standpipe pressure (SPP), fracture gradient, equivalent circulating density (ECD), and other well and fluid properties. AFO engineers also use workflows that provide guidelines to identify and manage events. These workflows were developed over years of drilling experience. For example, insufficient hole cleaning risk can be identified if the annular velocity, which is a function of hole size and pump rate, drops too low. Sag can be identified by an unexpected change in density.

The AFO engineer will monitor the sensors and manual test results from the rig or in a real-time operations center (RTOC) for any indication of an event. If the tools detect something questionable, the engineer will communicate with the rig in an intervention process. The system described in this paper has three types of interventions, which are color-coded to indicate priority. Green indicates the lowest-level priority, which is an information-only communication. A yellow intervention indicates a warning. A red intervention is a top-level intervention indicating the need for an immediate action.

Monitoring the signals involves watching multiple graphs that contain multiple plots for any sign of the outlined event indicators in the workflows. Although this work can be difficult and inefficient, a new algorithm has been developed to automatically notify the AFO engineer of any anomalies that may require intervention.

Process

The new algorithm can detect well abnormalities and provide automatic notifications to the AFO engineer. The AFO engineer can select a well characteristic to monitor, such as SPP, then perform a function on the parameter. For example, the engineer may be interested in monitoring SPP, and want to see the difference between the measured SPP and the value predicted by the drilling fluids modeling software. This system can monitor the difference between the actual and theoretical values. Other functions include the first derivative, integral of the signal, and pattern matching. It can also compare the signal to a preset value. The algorithm can also filter the data based on other parameters. For example, the AFO engineer may only care if the pressure is high when the flow is stable. In this case, the signal will be ignored if the flow is changing. The software can also smooth the data, using smoothing operations that include removing cyclical noise, averaging, and Hampel filter. The algorithm learns what normal behavior is for the output of the function. It calculates a score value to quantify how far from normal the signal is. If the score exceeds a user-defined value, the AFO engineer is notified. The engineer can then open the graphs and decide whether or not an intervention is needed.

The AFO engineer can also combine multiple scores, which enables monitoring for specific events. For example, the AFO engineer can monitor the difference between SPP and predicted SPP values and combine this function with erratic torque and decreased flow to monitor pack off. This method enables the algorithm to be used to automate the identification of events that are outlined in the workflows.

Examples

The first example of this algorithm is the detection of a greater difference between actual and predicted SPP values from the drilling fluids modeling software. An artificial increase in SPP is added in to show the score's reaction. Monitoring this difference can determine when the pressure is acting unpredictably, which is usually attributable to some unforeseen situation. Figure 1 shows actual pressure in blue and the predicted pressure in red. The sudden increase in actual pressure was added to the data to display the reaction in the score. The calculated score is shown in yellow. The two spikes in the score correspond to the sudden increase in actual SPP with no change in predicted SPP. Because this difference lasts long enough, the score returns to a low level as the algorithm becomes accustomed to what may be a new normal difference. The engineer has been alerted to the change and can take appropriate action if necessary. The time needed for the algorithm to settle into a new normal will depend on the amount of previous data the algorithm uses to calculate normal. It is worth noting that the measured and predicted SPP values have an offset during normal operations. This offset can be attributable to many factors, including incorrect or outdated parameters entered into the drilling fluids modeling software. The algorithm learns that this offset is a normal occurrence, and the score remains low. In this case, when that offset becomes larger or smaller, the score spikes. The engineer will be notified in either case.

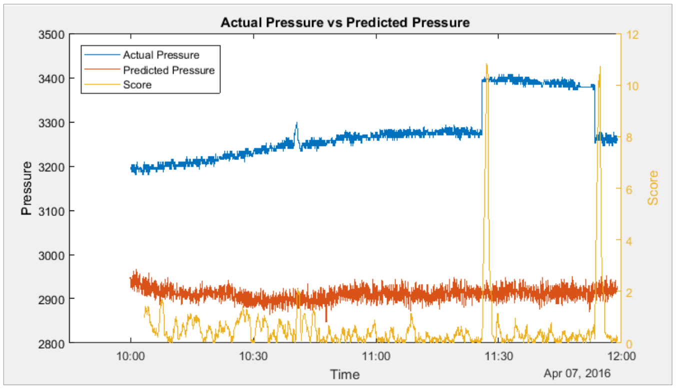

Figure 1. Actual vs. predicted pressure shown in blue and red, respectively. The score is a measurement of change in the difference between actual and predicted pressure.

The next example explores erratic torque. Erratic torque can be a symptom of many different issues, but discovering it visually is difficult. Figure 2 shows measured torque data with a short offset added. The blue line in Figure 2 indicates the measured torque, and the orange line indicates the score. Figure 3 shows the calculated erratic measurement. Although there are multiple ways to measure erratic behavior, it is measured by using variance in this example. As shown in Figure 2, the sudden offset in the torque value does not correspond to a spike in the score. This is because the score is based on an increase in erratic behavior, rather than in the actual torque value. However, a spike occurs at approximately 16:30, which corresponds to an increase in erratic behavior shown in Figure 3.

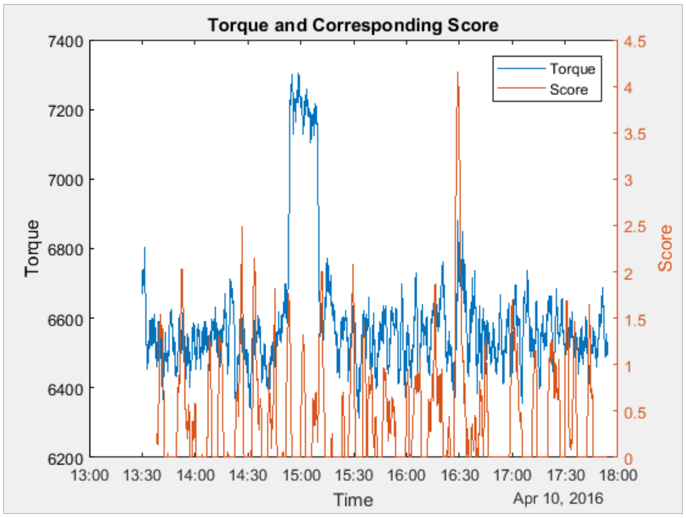

Figure 2. Torque (blue) and score (orange). The score is based on the erratic behavior of the torque.

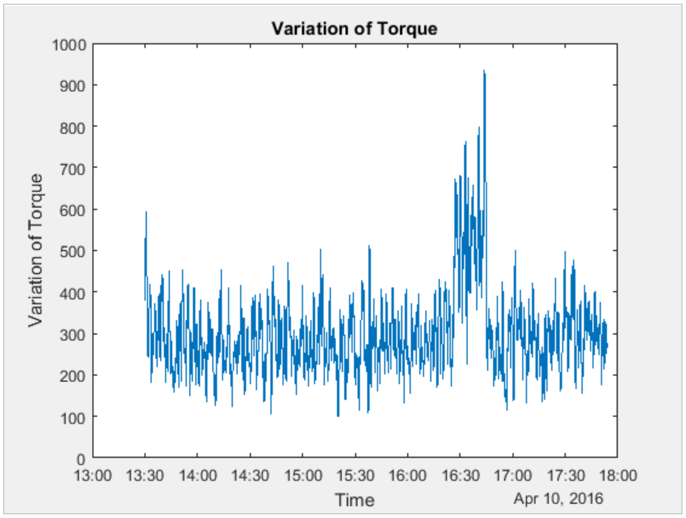

Figure 3. Measure of erraticism from the torque shown in Figure 2. The erratic behavior increases at approximately 16:30.

Figure 4 shows measured density data with an artificial increase and decrease added to the signal. The blue line indicates the actual density measurements. The red line shows the predicted value, and the yellow line indicates the calculated score. An artificial increase, then decrease, in density is added to the data to show the reaction of the score. In this example, the score is calculated using the difference between the actual and predicted density values above a preset value. In this case, the preset value is 0.5 lb/gal. As shown in the figure, when the difference reaches a sufficiently high value, the score spikes and remains high until the density difference decreases again. Unlike the pressure difference shown in Figure 1, the score remains high and does not settle.

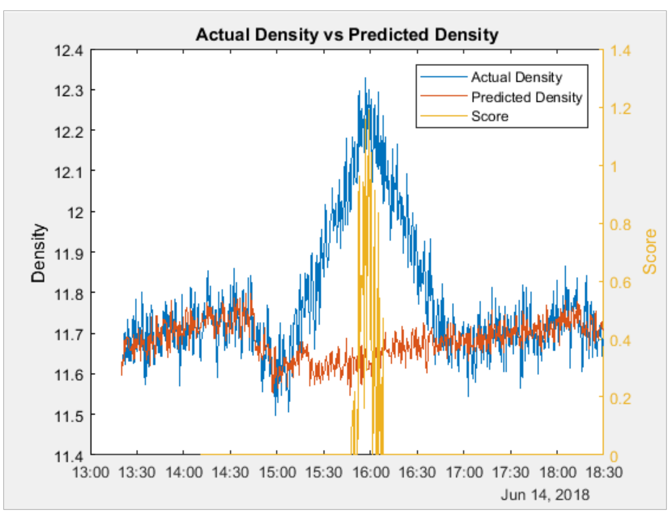

Figure 4. Actual vs. predicted density shown in blue and orange, respectively. The score, shown in yellow, is calculated using the difference between the actual and predicted densities with respect to a set limit of 0.5 lb/gal.

Figure 5 shows the score calculation based on a decrease in annular velocity. This is measured data with an artificial decrease in the value to show the score reaction. In this case, the score is calculated by how far below the preset value the signal is. The preset value is set to 145 ft/min. The decrease in annular velocity corresponds with a spike in score. Note that the increases in annular velocity do not cause a change in the score.

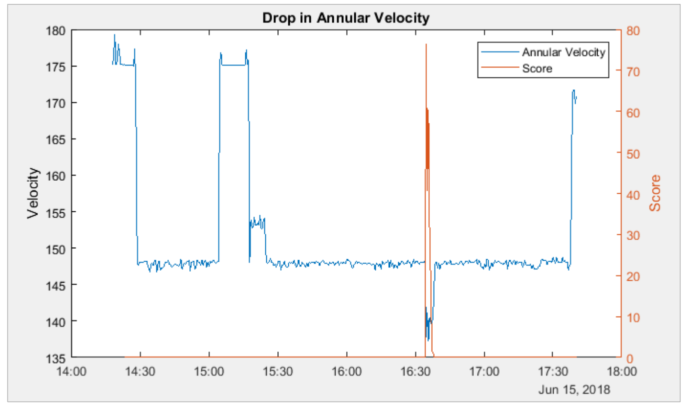

Figure 5. Annular velocity (blue) and corresponding score (orange). The score is based on the how far below a preset value, 145 ft/min, the annular velocity drops.

In Figure 6, the score is based on the slope of the ECD signal. This is a measured ECD value without modifications. Figure 7 shows the calculated slope of ECD.. There are two spikes in the score. The first is larger than the second, despite the higher ECD value. The spikes in the score correspond to the higher slope values shown in Figure 7.

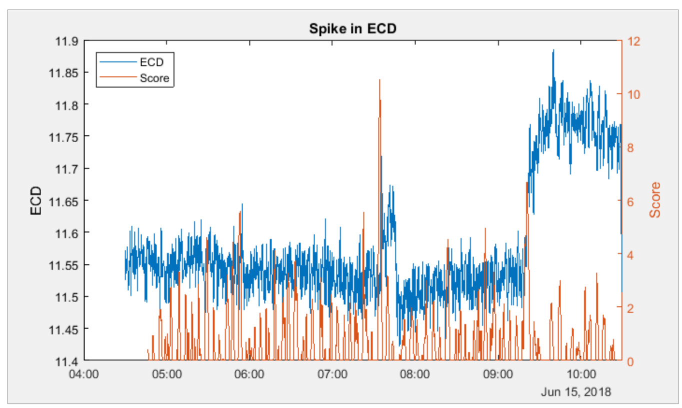

Figure 6. ECD (blue) and the corresponding score (orange). The score is based on the rate of change of the ECD signal. The graph of the slope of ECD vs. time is shown in Figure 7.

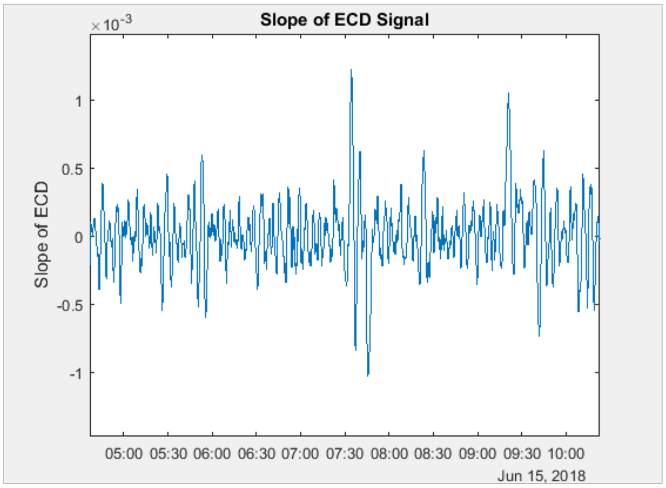

Figure 7. Slope of the ECD signal shown in Figure 6. The two spikes shown in Figure 6 correspond to the two sudden increases shown here.

Figure 8 shows multiple scores that can be combined using a weighted average to identify specific conditions as shown in Figure 9. These scores are calculated from actual data. According to the documentation associated with this data, the AFO engineer triggered an intervention at 10:30. The algorithm would have alerted the engineer to the same conditions.

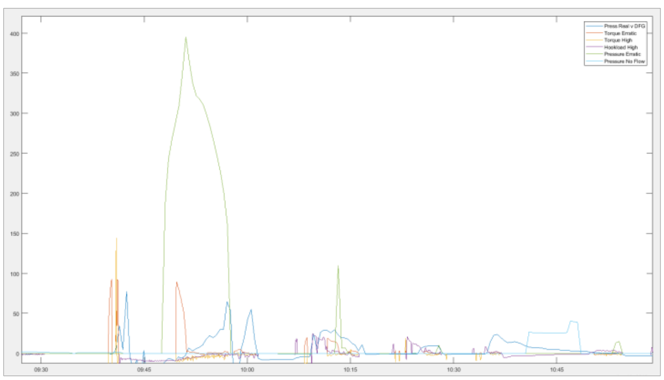

Figure 8. This graph shows the many scores that can be accumulated to identify a specific event.

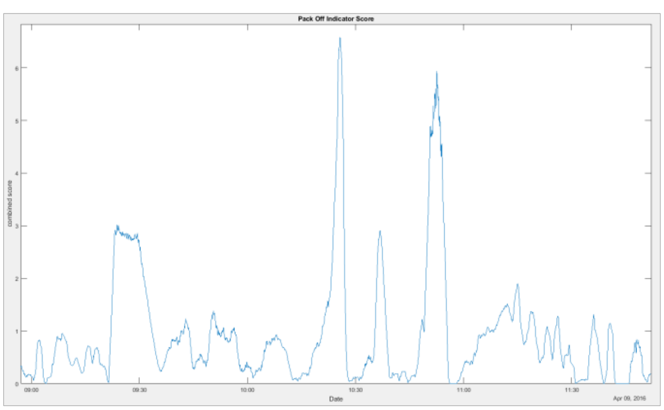

Figure 9. Average scores combined. The spikes in the score correspond to interventions from the AFO engineer.

When running this algorithm with documented interventions, the software identified all interventions. It is not possible to calculate how many false positives occurred because many different unknown actions could have resulted in the unusual signals. For example, the engineer may have noticed the unusual signals, communicated with the well personnel, and learned they were doing something that was normal. In another example, the high score may have occurred after another intervention, which could have been caused by fixing the previous intervention. It is also difficult to identify the time at which the engineer intervened because their reports can be an approximation of the time that they noticed the issue.

Conclusions

The use of this algorithm enables AFO engineers to be alerted to any unusual signals. This functionality makes it possible for them to monitor multiples well at a time and to quantify the severity in real time. Because the operations and signals that are being monitored can be selected by the engineer, the algorithm can be customized to address the specific needs of a well.

Acknowledgements

The author would like to thank Halliburton for providing support and structure to accomplish this work. The author specifically thanks Dale Jamison, Aidan Porter, and Vitor Lopes Pereira for help along various points in this work.

Nomenclature

AFO = *applied fluids optimization*
ECD = *equivalent circulating density*
RTOC = *real-time operations center*
SPP = *standpipe pressure*

References

1. Skogdalen, J.E. and Vinnem, J.E: "Quantitative Risk Analysis of Oil and Gas Drilling, using Deepwater Horizon as Case Study." Reliability Engineering & System Safety, v. 100 (April 2002) 58-66.
2. Jenkins, P.B. and Crockford, A.L.: "Drilling Costs." SPE-5266-MS, SPE European Spring Meeting, London, UK, April 14-15, 1975.
3. Iyoho, A.W., Meize, R.A., Millheim, K.K., and Crumrine, M.J.: 2005. "Lessons From Integrated Analysis of GOM Drilling Performance." SPE Drilling & Completion, v. 20, No. 01, March 2005.
4. Lukawski, M.Z., Anderson, B.J., Augustine, C., Capuano Jr., L.E., Beckers, K.F., Livesay, B., and Tester, J.W.: "Cost Analysis of Oil, Gas, and Geothermal Well Drilling." Journal of Petroleum Science and Engineering, v. 118 (June 2014) 1-14.
5. Gyllensten, A., Salem, A.A.N., Coleman, J.T., Ali, W., Russell, R.B., Nabawy, S.M., Grayson, H. Youssef, F., Ragheb, O. Kalathingal, P., and Nair, R.: "Towards an ADCO Real-Time Operations Center." SPE-101486-MS, SPE Abu Dhabi International Petroleum Exhibition and Conference, November 5-8, 2006.
6. Galliano, C. Rand, A., Sparling, S., and Watson, P.: "Automating Drilling Fluid Analysis." Offshore Engineer, April 1, 2016.