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Manage by exception: a practical way to reduce cost and improve performance

With a few considerations, today's data-centric workflows can be enhanced with the introduction of MBE, reducing risk and cost.

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Manage by Exception (MBE) is a term often associated with business management activities, where a plan is put in place and then the process carries on until there is a variation that is severe enough to warrant some level of intervention. When taken outside of the business management realm, we see that MBE principles are a key concept in efforts leading supervised, semi-automatic or even automated processes.

MBE may sound like a high-technology activity that can become very complicated with the risk of costing as much as it saves. However, there are many proven cases where MBE principles can be applied, starting with low-fidelity and even intuitive steps that bring about massive savings and reduction of risk. To understand how to get started on MBE principles, let's consider a simple example.

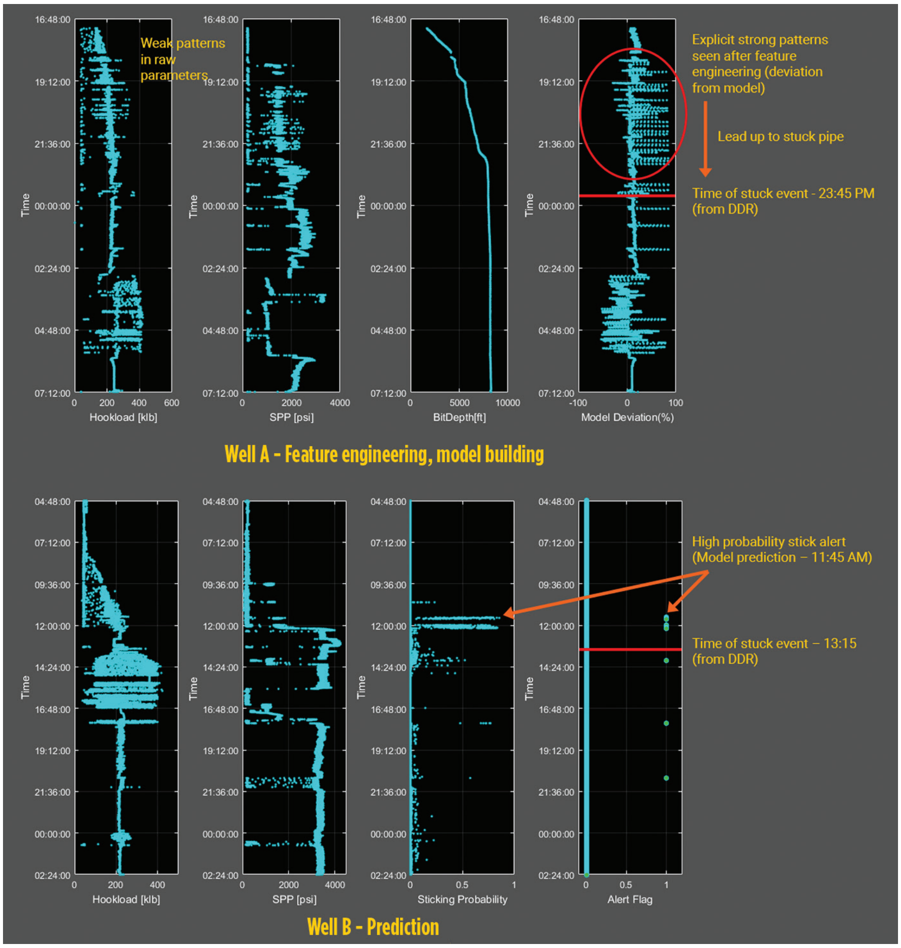
Many of us drive cars that have land-departure warning. This is an autonomous system on the vehicle that uses built-in cameras to detect the edges of the lane you are driving in. In operation, this system monitors the lane and warns the driver as they approach the edges.

This simple example helps us to understand the basic building blocks of MBE:

1. A plan. To stay in the identifiable lane.
2. A violation. These are the rules that define how the plan may be interrupted. In the example, this is when the car approaches the lane boundary as identified by the camera and software on the car.
3. Defined actions. The system will notify parties of the violation.

When applied to the oil and gas industry, there are many ways that we can implement these simple concepts that have huge potential for improvements in accuracy, higher quality, safer operations and even cost savings.

Fig. 1. Raw hookload patterns, compared with an advanced analytical model (see stuck pipe graphic).



MBE-ASSISTED DATA MANAGEMENT PROCESSES

Let's consider a real-world example of MBE principles used in a data management workflow. In this case, a data management company provides cloud-based solutions allowing their clients to aggregate and assemble the data produced in real-time, from a variety of services that collectively make up the drilling activity. Each sub-contractor (or service company) provides information in their own timeframe using a variety of data formats. The challenge is to have this data aggregated and measured for timeliness and completion to provide a simple assessment, measuring whether the data is suitable to be used in monitoring processes.

If the data management company uses manual processes, then they have individual real-time operations personnel manually monitoring the data as it is transferred. These operations personnel are typically looking for data gaps or values that are outside of expected normal ranges. When an issue is detected, the time, data, context and type of problem is recorded for reporting purposes.

When migrating to MBE processes, the rules that have been identified are:

- The client expects to have data at regular intervals. Let's say five seconds for a given set of data streams.
- Further (for timeliness), the client expects that data is no later than some defined time delay. For this example, let's say that the client processes will accept data that is one minute behind real-time.
- Lastly, the client expects the data to be above a known minimum and below a known maximum representing the limits of the sensor being measured or the environment that the sensor is operating within.

By implementing these rules, a subsystem is created, monitoring each data stream, from each service provider, in real-time. When an exception is detected, it is reported to the operator of the real-time center through an alert system. This automated system removes many of the tedious steps from monitoring for issues, and allows data specialists to focus on correcting issues as they are detected.

MBE APPLIED TO REAL-TIME ENGINEERING

Next, let's consider an engineering process where we are applying MBE principles, along with analytical analysis of real-time data. In this class of process, we combine the analysis of real-time parameters with the active monitoring of MBE. The objective is to provide advance warning that the drilling activity is likely moving toward some undesirable event that would adversely affect the drilling process, the quality of the wellbore or the safety of the activity.

Using conventional processes, an engineer (or team of engineers) would monitor real-time data from either the service providers, the rig or the data platform described above. Using their knowledge and any number of software systems, they monitor the drilling situation, looking for sub-par performance and attempting to react based on their knowledge and experience. This is effective, but requires real-time data, a high level of knowledge about the drilling environment and expert engineering analysis, all occurring in real-time.

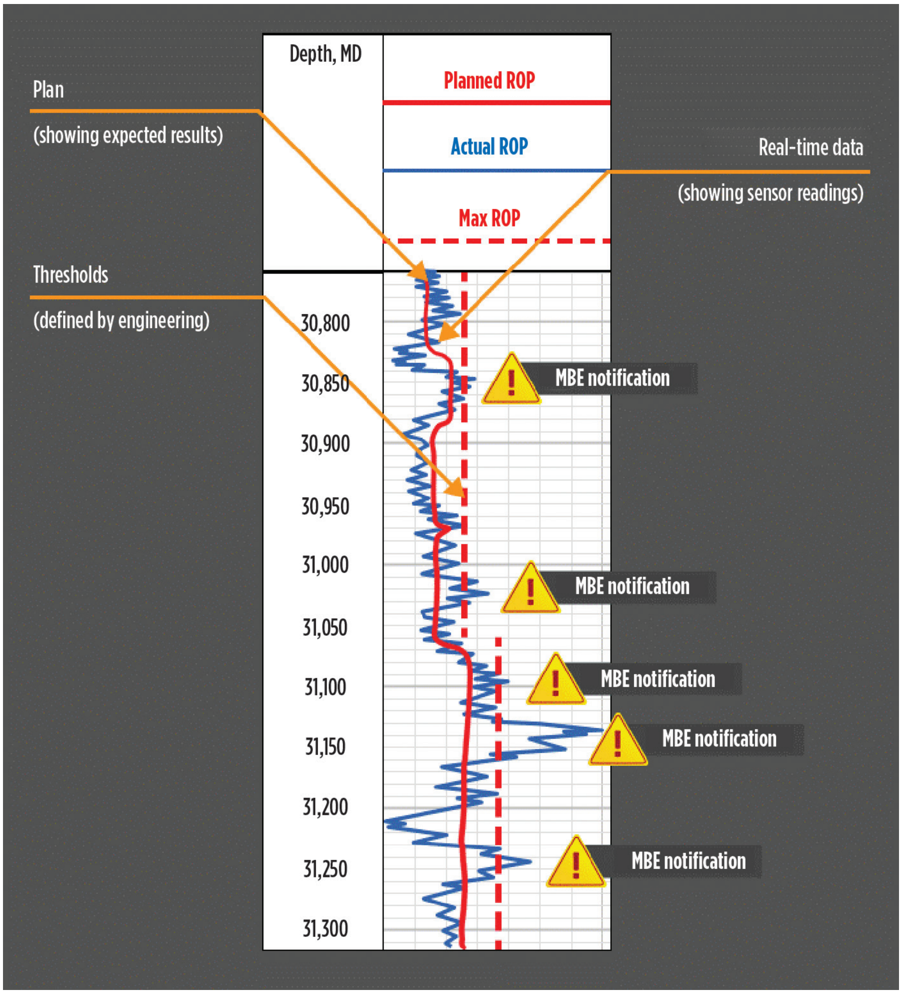
Bringing MBE processes into this engineering workflow is best achieved by also introducing predictive analytics, such as Machine Learning (ML). When using predictive analytics, the system monitors any number of real-time channels for patterns hidden in the data. These patterns define the probability of the undesirable event occurring. The MBE process then uses the probability as a baseline. Once the probability exceeds a threshold, the engineering team is notified and able to get involved.

In a recent case study, compiled by a data sciences team working on behalf of an independent oil company, they applied machine learning processes to monitor a variety of characteristics that contribute to stuck pipe. Each real-time parameter on its own is insufficient to provide advance warning of stuck pipe. But, when taken together, they were able to proactively monitor the engineering data.

As shown in Fig. 1, the image on the top indicates a traditional examination of the hookload data. There is an elevated variance, but it is insufficient to provide with high confidence that there is a problem. The image on the bottom examines multiple parameters and looks for variations from the statistical norm, which increases the likelihood of a stuck-pipe scenario. The explicit model (on the bottom) determined a high probability of stuck pipe conditions almost three hours prior to the actual condition occurring. In an automated system, the ML predicts the likelihood and the MBE system notifies the engineers. This combination allows the engineers to focus on corrective measures and removes them from the more tedious processes of identifying these undesirable events.

MBE principles can apply to any type of analytical process. However, they are much more beneficial when the output of an analytical process can be consumed

Fig. 2. Planned versus actual ROP with MBE notifications.



by the MBE complex event engine to look for logical comparisons.

ADVANCED ENGINEERING

Another example of how MBE can bring value is being pursued by a different independent oil company in their global operations, where they want to automate process safety and efficiency using MBE. They have designed a series of algorithms that monitor a single factor in real-time.

Examples include monitoring the influx, or decrease, in fluids—including compensation for wave action (when offshore); monitoring of micro-stalls in mud-motors that lead to failure; over- or under-torque of connections contributing to fatigue or failure; and optimal rate of penetration (ROP) based on offset wells, **Fig. 2.** Then, in its real-time operations centers, the notification through MBE is provided as a constant display. This workflow has allowed them to monitor more wells with a higher degree of confidence, more lead time to avoid issues, and more effective use of limited engineering resources.

LESSONS LEARNED

The above three examples point out how MBE, or MBE coupled with prescriptive or predictive analytics, brings about gains in efficiency and reduction in risk.

There are several considerations for the company embarking on MBE and analytics as an augmentation to traditional engineering principles.

First, any analytic or rule-based system is highly dependent on data. If the real-time data fed into the algorithm or process is of degraded quality, then the outcome of the process will result in false-alarms or misguided suggestions.

Second, access to information is important. Each of these examples is based on an assumption that data is available as needed, and in formats that the analytics or MBE processes can operate against. It is recommended that these processes be designed on a data platform that supports industry standards to ensure the highest level of data availability.

Lastly, accuracy must be considered. Any system or process that is highly variable will result in false alarms or misunderstandings. These processes often require a level of "tuning" as they are being designed, as well as when they are in operation. The best use of MBE principles is one where the system is monitored and adjusted as needed, to ensure the highest level of responsiveness and accuracy.

With these conditions and some logical thinking, many of today's data-centric workflows can be enhanced with the introduction of MBE, bringing about a reduction in risk and cost. WO

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