Detection of Failures and Interpretation of Causes During Drilling Operations

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Abstract

A majority of the remaining oil and gas reserves are located on continental shelves. Offshore drilling operations are expensive, and the numbers of wells are therefore few, long and complex. The number of process failures seen in recent years does not exhibit the intended declining tendency. A failure during drilling operations is defined as the state when non-productive time is occurring.

The motivation behind the work presented here is to advance a specific computerized method for helping the petroleum industry in reducing unwanted downtime. More up-time is needed. The ultimate goal of our research is to improve the drilling process quality and efficiency. This is achieved by first detecting process deviations (symptoms) during the drilling process, and produce explanations generated by a general knowledge model (ontology). The symptoms have been translated into formal concepts and related into cause-effect relationships with errors and failures.

Our experimental system is able to read data from a drilling process and apply the on-line detected and predefined static symptoms to capture a probabilistic understanding of the downhole process. We will demonstrate the tool's ability during selected drilling processes to determine which failure type is the most threatening during problem situations and which errors are causing the failure. The failures revealed by the tool on basis of detected symptoms are compared with the reported failure in the field.

Introduction

A majority of the remaining oil and gas reserves are located on continental shelves. Offshore drilling operations are expensive, and the numbers of wells are therefore few, long and complex. The number of process failures, defined as states when non-productive time is occurring, seen in recent years do not exhibit the intended declining tendency. Similarly, process data are gradually improving in quality, but the sheer amount is a challenge.

To improve the drilling process quality and efficiency one solution is to advance a specific computerized method for helping the petroleum industry in reducing unwanted downtime. In the work reported here, this is being achieved by detecting process-deviations (symptoms) during the drilling process, and applies them to produce explanations and advices, supported by a general knowledge model (a drilling ontology). The
symptoms have been translated into formal concepts and then interrelated through cause-effect relationships in pathways linking causes to related failures.

Our experimental system is able to read data streams from a drilling process and apply the on-line detected symptoms together with predefined static symptoms to capture a probabilistic causal interpretation of the downhole process.

The tool demonstrate its ability to determine which failure type is the most threatening during problem situations and which errors are causing the failure. Experiments showed that failures revealed by the tool were identical to the reported failure in the field.

**Previous experience**

Knowledge-building ontologies

Established results from the community of knowledge acquisition and modeling have produced several methodologies and techniques for describing knowledge at a conceptual, implementation-independent level. Influential examples are the Components of Expertise Framework (Steels 1990), and the CommonKADS methodology (Breuker and Van de Velde 1994). To promote re-using of such models, the call for common generic models – more frequently referred to as ‘ontologies’ –has led to the development of generic knowledge models within different application areas (Klein and Smith 2010). Correspondingly, the term ‘ontology engineering’ is now often used instead of ‘knowledge modeling’. A large ontology that has become an international standard within the oil industry is the ISO 15 926 ontology (Fiatech 2011). This ontology has been an inspiration for our ontology as well, although the large cover and the high complexity have led us to develop our own.

Process surveillance

Over the last decade, several competing process surveillance tools have emerged. Two tools from within the process of oil well drilling are DrillEdge (Gundersen at al. 2012) and e-drilling (Rommetveit et al. 2012).

DrillEdge is a software system that provided decision support based on case-based-reasoning applied on real-time drilling data (RTDD). DrillEdge was developed to reduce the cost and decrease the probability of failures in oil well drilling. DrillEdge continuously monitored around 10-40 oil well drilling operations commercially for several years. Ideas from DrillEdge is now being developed under the name of Drillytics and Drillmetrics (http://datacloud.com).

e-drilling is also a decision support system which performs automatic supervision. Dynamic models calculate the well conditions, based on all available data from the drilling process, and provide diagnostics in the form of warnings and advice. Forward looking capability based on trends can give early warning of near-future error situations.

**Theory**

Ontology Engineering

Ontology is a term used in philosophy, encompassing the study of "what is". The application of Ontology within information technology and Engineering is more recent, and has replaced and / or enhanced terms like knowledge model, data model, term- catalogue, etc. All ontologies make some assumptions about the world they represent.

The model of drilling-related knowledge developed as part of this research is based on the adaptation of established methods and best practice for knowledge model development. The term "knowledge" –as used in this paper – refers to all types of explicitly represented structures on the basis of which a system is able to perform reasoning (Aamodt 1943). Our model of general domain knowledge consists of concepts and cause-effect relations between them, organized in a hierarchical ontology model. A concept may be a
general definitional or prototypical concept, and may describe knowledge of domain objects. A network view to concept definition is taken, in which each concept is defined by its characteristics and by its relations to other concepts.

In our ontology, as in most ontologies, the top-level concept Thing stands for anything in the world worth naming or characterizing. Everything we want to talk about is a subclass or instance of Thing. Thing has three subclasses; Entity (an actual thing in the real world), Descriptive Thing (a description or representation of an Entity) and Relation (a bi-directional relation between concepts). The model can be viewed as a three-level model below the mentioned top-level. The upper level consists of generic concepts, such as Physical Object, Mental Object, State and Process. Our ontology is a domain-specific ontology, however, in which Thing is synonymous with the concept Drilling Process. Figure 1 demonstrates a drilling situation and indicates common engineering concepts in the medium level.

![Figure 1—Important concepts within the drilling process](image)

Below the top level in the ontology, the medium level consists of domain-specific concepts, such as Cement Pump, WOB Low and Shale Swelling, while the bottom level of the model contains specific facts obtained from situation-specific incidents (failure cases). Initially, a top-down modeling approach has been taken, developed from textbook and in-house expertise knowledge. In an upcoming stage of the project the ontology will be improved by allowing a bottom-up approach by utilizing the specific knowledge obtained from situation-specific failures. This activity will eventually incorporate new knowledge and thus a refinement of existing model.

**Research motivation**

The main objective of bringing ontology engineering into play is its ability of combining observed symptoms and potential error states. This manner of establishing the most probable error and failure type, applying ontology for on-line surveillance in the oil-drilling domain has, to our knowledge, not been tried before. However, more applications of ontology for the purpose of on-line surveillance in other domain do exist, for example the BioStorm system developed as part of DARPA’s national biosurveillance technology program (Crubezy et al 2005). In most of these applications the errors or failures occur at a high frequency, while the error frequency during our proposed application within the drilling process is typically only a few failures...
pr. month. To compensate for the lack of a large data volume, a rich knowledge model is therefore necessary. Our ontology contains more than 1 500 concepts.

**Practicalities and definitions peculiar to our ontology**

A syntactical regime of the ontology is that the first letter in each word of a concept is written with capital letter while relations between concepts are written solely with small letters, e.g. has subclass. To support the reader in understand the notion of our ontology, Table 1 and 2 present some snap-shots of our model. In Table 1 typical concepts are defined, while Table 2 exemplifies relationships between concepts. To make the modeling process more transparent, concepts are grouped vs. their role:

- Error concepts are indicated as such by adding (err) to the concept
- Failure concept are indicated by adding (f) to the concept
- Static symptoms are indicated by (ss). There are symptoms which are known before drilling starts. Their value or state are read from the drilling plan or from the EoW reports or guessed by an expert
- Symptoms(s) are data agents, detectable in the real time data..
- Internal parameters (i) are non-observable. These concepts exist only in the ontology, but enhances it substantially

<table>
<thead>
<tr>
<th>Concept</th>
<th>Concept Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Csg Ann P High (s)</td>
<td>Measured (and interpreted) pressure in casing annulus A or B</td>
</tr>
<tr>
<td>Csg Ann Slot Narrow (ss)</td>
<td>When &lt; 2 - 1.5 - 1.0 in → three levels of narrowness</td>
</tr>
<tr>
<td>Csg Collapse (f)</td>
<td>Insufficient casing strength. Collapse under large external pressure and low internal pressure</td>
</tr>
<tr>
<td>Csg Erosion (err)</td>
<td>The inside of the casing is eroded. Reduced thickness reduces its strength</td>
</tr>
<tr>
<td>Cuttings Bed Compact (i)</td>
<td>The bed solidifies slowly over time and due to high amount of fine, sticky particles</td>
</tr>
</tbody>
</table>

**Table 1—Definition of five selected concepts (starting with the letter C)**

<table>
<thead>
<tr>
<th>From-concept</th>
<th>Relation strength</th>
<th>To-concept</th>
</tr>
</thead>
<tbody>
<tr>
<td>Csg Ann Slot Narrow (ss)</td>
<td>0.6</td>
<td>Cement Sheath Quality Low (i)</td>
</tr>
<tr>
<td>Csg Erosion (err)</td>
<td>0.4</td>
<td>Direct Factor Behind Csg Collapse (x)</td>
</tr>
<tr>
<td>Cuttings Bed Compact (i)</td>
<td>0.6</td>
<td>Cuttings Bed Erosion Low (i)</td>
</tr>
<tr>
<td>Cuttings Bed Erosion Low (i)</td>
<td>0.8</td>
<td>Cuttings Concentration Low (i)</td>
</tr>
<tr>
<td>Cuttings Concentration High (i)</td>
<td>0.2</td>
<td>Accumulated Cuttings (err)</td>
</tr>
<tr>
<td>Cuttings Concentration High (i) AND Enlarged (i)</td>
<td>0.8</td>
<td>Accumulated Cuttings (err)</td>
</tr>
</tbody>
</table>

**Application of the method**

A continuous surveillance of the drilling process by means of ontology engineering has the purpose of revealing potential failures and identify which error is causing the failure.
Failures during drilling

Figure 2 presents some errors and failures in the drilling process, classified in accordance with the physical location of occurrence; either a) inside the wall of the sedimentary formation, b) in the wellbore or c) in the equipment. This simple-to-accept manner of subdivision makes errors and failures easier to classify.

Error is a State in which a Process or a Facility are less functional or stop functioning, but do not necessarily cause any significant loss of time. An error occurs when a parameter, a process or an object exhibit an unwanted deviatory performance, while a Failure is a State in which a significant unplanned stop in the process occurs; resulting in a Repair State, and thus a significant NPT is involved.

Figure 3 presents the most common failures during drilling of 427 offshore wells, drilled in the period between 2004 and 2010 (Pritchard et al. 2012). The data were re-structured by us to specify the data better to include all failure types presented in Figure 2. Pritchard et al. (2012) reported Stuck Pipe as one failure group, but split in two parts (with different weight) by us into Differential and Mechanical stuck. Wellbore instability failures were also split in two: Chemical and Mechanical instability. The lump group called Equipment Failures was split in 7, in decreasing probability-order: Motor Stall; Rotary Steerable Failure; MWD Failure; Bit Malfunction; DS Washout; DS Twist Off; Casing Collapse. The groups Rig Failures, Wellhead Failures and Other Failures were deleted from the Pritchard-list since these failures are presently not in our model.
Process surveillance

During a drilling operation the expected state of the operation is Normal; the operation is performing as expected. As soon as a symptom is detected, the operation turns into temporary error state as shown in Figure 4.

Figure 3—Failure distribution of 427 offshore wells (modified from Pritchard et al. 2012)

Figure 4—Tree possible process states during drilling. Encountering a symptom will shift the operation from Normal to Error State. Most of the symptoms are vanishing (self-rectifying) during the process, bringing the process back from the Error State to the Normal State (Skalle et al. 2014)
Supporting data and information during surveillance
The symptoms utilized for failure detection are of two types:

Static symptoms (ss)
Dynamic symptoms (s)

Static symptoms are generated on basis of already available data before drilling the section, as exemplified in Table 3. On basis of existing data, static symptoms are built as exemplified in Table 4.

Table 3—Six selected static data types from the ongoing operation, placed in rows and columns

<table>
<thead>
<tr>
<th>Row</th>
<th>Data</th>
<th>Description of data Type</th>
<th>OFU (F column)</th>
<th>SI (H column)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>Bit Type</td>
<td>2 options: Shear or Roller bit</td>
<td>Shear Bit</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Bit Size</td>
<td>The previous section</td>
<td>17,50</td>
<td>0.44</td>
</tr>
<tr>
<td>7</td>
<td>Bit Size</td>
<td>Present section</td>
<td>12.25</td>
<td>0.31</td>
</tr>
<tr>
<td>8</td>
<td>Bit Teeth Length</td>
<td></td>
<td>2.00</td>
<td>0.05</td>
</tr>
<tr>
<td>9</td>
<td>Fm above CS charged</td>
<td>2 options: Yes or No</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>Fm Special Expected</td>
<td>2 options: Yes or No --&gt; Yes; Cod Fm Unstable</td>
<td>Yes</td>
<td></td>
</tr>
</tbody>
</table>

Table 4—Seven selected static symptoms (of totally 34) generated by data in Table 3. When three values are seen in the Definition column the actual symptom is differentiated into three strength-levels

<table>
<thead>
<tr>
<th>Static symptom</th>
<th>Definition</th>
<th>Main input parameter</th>
<th>Available</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bit Aggressive</td>
<td>When Bit Teeth.Length &gt; 15 mm</td>
<td>H11</td>
<td>0</td>
</tr>
<tr>
<td>Bit Type Shear Bit</td>
<td>When Bit.Type = Shear Bit</td>
<td>F5</td>
<td>1</td>
</tr>
<tr>
<td>Build/Drop Section Inside Csg</td>
<td>When (MD.Csg.Shoe) - MD.Build/drop upper &gt; 0</td>
<td>H20-H17</td>
<td>1</td>
</tr>
<tr>
<td>Build/Drop Section Inside Openhole</td>
<td>When (MD.Csg.Shoe - MD.Build/drop lower) &lt; 0</td>
<td>H20- H18</td>
<td>0</td>
</tr>
<tr>
<td>Cement V/Theoretical V Low</td>
<td>When Ve/Vc.th &lt; 1.5 - 1.25 - 1.0</td>
<td>H33/H34</td>
<td>1</td>
</tr>
<tr>
<td>Csg Ann Slot Narrow</td>
<td>When (Bit.Size - OD.Csg) &lt; 4 - 3 - 2 in</td>
<td>F6-F27</td>
<td>0</td>
</tr>
<tr>
<td>Fm Above Charged</td>
<td>Here 1 – yes. Increasing reservoir pressure due to natural fracture in the formation or drilling fluid entering the reservoir through later induced fractures</td>
<td>F9</td>
<td>1</td>
</tr>
<tr>
<td>Fm Special Expected</td>
<td>Here 1 – yes</td>
<td>F10</td>
<td>1</td>
</tr>
</tbody>
</table>

Dynamic symptom: We have developed 16 agents so far and tested them against historical drilling data and accepted them when the hit rate was > 75%. Here are five (or 8) agents:

Activity Of Drilling
Activity Of Tripping In (or Out)
Cuttings Initial Concentration High (or Low)
ECD-Frac D Low
ECD-Pore D High (or Low)

Dynamic symptoms are automatically detected in the RTDD as indicated in Figure 5. The dynamic symptoms represent the starting point of a relationship path leading via an error to a failure. However, a symptom may point not only at one but numerous failures.
Developing and testing

On top of the ontology a reasoning system was built. In earlier work we have shown how to utilize specific cases supported by general domain knowledge through a process called knowledge-intensive case-based reasoning (Aamodt, 1993, 2004). More recent work (Skalle and Aamodt 2004, Skalle et al. 2013), like work reported here, focus on reasoning within the ontology.

In our tool, we applied the Creec model (Aamodt 2004) as a tool for developing ontologies. We transferred the resulting ontology model to an Excel spread-sheet in order to be able to include logical operators like AND, OR and IF, in our tool, and thus develop a more versatile ontology. In order to estimate and compare failure-probabilities, path strength of each single path is a product of the strength of all n relations leading from our observation (symptoms) to the target failure:

\[
\text{Path strength} = \prod_{i=1}^{n} (\text{Relation Strength}_i)
\]  

(3)

The sum of all paths pointing to a specific failure, defines explanation strength of a failure:
Explanation strength = \sum_{j=1}^{n-1} \text{Path Strength}_j \quad (4)

Here \( n \) is the number of relations in a path and \( m \) is the number of paths of each failure. Calculated explanation strengths serve as a good measure for identifying probability of failure \( k \):

\[
p(\text{failure } k) = \frac{\text{Explanation Strength failure } k}{\text{Total Explanation Strength all failures}} \quad (5)
\]

To prepare the model to best be able to point out the most probable failure, a final fine-tuning of the model is presented next.

In addition to structural relationships (e.g. has subclass) the model consists purely of causal relationships. Every relationship is bi-directional, e.g. each ‘causes’ relationship has an equally strong ‘is caused by’ relationship. By including both relationship types the existing list becomes twice as long. To avoid any loops, the relationships, now consisting of ‘causes’ and ‘caused by’ relationships were rectified in a strict manner, starting from symptom concepts, (s) and (ss), moving in one direction and ending at failure concepts (f).

It was necessary to fine-tune the ontology model to replicate the reported failure distribution shown in Figure 3. The pre-test was performed by simultaneously activating all possible static and dynamic symptoms and observe resulting failure distribution. To replicate the global occurrence distribution it was necessary to include prior frequency probabilities of each static and dynamic symptom. Each symptom was given an occurrence-frequency as shown in Table 5. E.g. the symptom Torque Erratic occurs statistically only once in every well \( (p = 0.1) \), while a kick occurs seldom in every well \( (p = 0.05) \).

<table>
<thead>
<tr>
<th>Expected occurrence frequency</th>
<th>pp</th>
</tr>
</thead>
<tbody>
<tr>
<td>Once in every well section</td>
<td>1.00</td>
</tr>
<tr>
<td>Seldom in every well section</td>
<td>0.50</td>
</tr>
<tr>
<td>Once in every well</td>
<td>0.10</td>
</tr>
<tr>
<td>Seldom in every well</td>
<td>0.05</td>
</tr>
<tr>
<td>Once in every 10\text{th} well</td>
<td>0.01</td>
</tr>
</tbody>
</table>

The resulting distribution of failures of the final fine-tuning test is presented in Figure 6.

Figure 6 shows that the basic model is very similar to the historical failures. We can now claim, with a certain confidence, that our ontology represent all failures in consistence with field observations. In the next step we remove all prior probabilities and expose the model to real life failure cases.
Results

The EoW report is the main source of information, both for determining static and dynamic symptoms, and for finding real failure cases. A case template was created to make the process of creating cases smooth and streamlined.

It is fair to say that at this stage we obtained somewhat disappointing results, and will therefore present only one case. Summary of event during the 12 h period prior to the motorstall:

Pre-activities: MD to 5845 m MD were influenced by hard stringers with adjacent soft shale. Due to this a slight deviation from well path occurred. At 5845 m MD the AC motor on the DDM (derrick drilling machine) had to be changed. BHA was pulled back into the 9 5/8” csg shoe while repairing the DDM. While tripping back in pack off tendencies, increased circulation and cleaning caused a malfunctioning of the MWD tool. Re run with new MWD tool.

Case 2: Drilling ahead from 5845 m MD a series of long and hard stringers were drilled. From 6068 MD to 6133 m MD a massive hard formation was drilled with an average ROP of 2 m/hr. Torque and ECD reading increased, and it was necessary to stop circulation and reaming in order to avoid further motor stalling. A combination of WOB and RPM was used to reduce stick-slip in this zone but at 6075 m MD the RSS (Rotary Steerable System) tool stopped transmitting.

During this period we gathered all possible static and dynamic symptoms as shown in Figure 7. Failure distribution was then estimated each time a new symptom appeared and shown in Figure 8. The last detected symptom (pressure spike) occurred at 17:00, 2.5 h before Motor Stall. Figure 8 shows how the Motor Stall probability starts around its typical occurrence-probability of 6.8 (see Figure 3), and ends at 18%.

![Figure 7—Timeline of the events leading up a motor stall failure. The box to the left shows that 15 static symptoms were present from the start. Then 14 dynamic symptoms appeared before a Motor Stall occurred at 19:30](image)

![Figure 8—Evolution of motor stall probability vs. incoming symptoms over a 12 h period](image)
Figure 9 represents the distribution of all potential failures at the time of the last observation (pressure spike) before failure. Here we see that Motor Stall is the most probable failure, but not sufficiently distinguished from the other failures to claim that we saw it coming. The research is, however, still immature and slowly progressing.

![Figure 9—Failure distribution 2.5 hours prior to failure](image)

The most obvious reason for not seeing the failure clearer is that too few relevant symptoms are available. We need to detect more symptoms (assuming they are present and detectable in the data). Sensitivity of the agents to deviations in the RTDD must increase.

Besides of missing symptoms, the other main reason is the quality of the ontology. However, its design and the spreading of pathways from symptoms to failures stay firm. The model content has not yet been tested against sufficiently many real cases. A bottom-up testing will reveal clues of how to re-design and how to adjust existing model.

Another necessary adjustment is that some of the dynamic symptoms must decay after detection. Some symptoms, like Well Pressure Low, could in many situations be allowed to stay active throughout the complete section. Geographical symptoms like Fm Soft, can be true only locally in the well at the depth of occurrence, while fluctuating parameters like Torque Erratic should only last for some minutes after its occurrence. Latter type of symptoms, the short lasting, should be equipped with a decaying characteristic.

**Conclusion**

After having developed an ontology of the complete drilling process and having tested its response to real failure cases, these conclusions can be drawn.

- The ontology of the drilling process was able to reproduce a typical offshore failure distribution after simultaneously being exposed to all the symptoms, 34 static and 35 dynamic. All symptoms were in this pre-test equipped with their probable frequency of occurrence
- When tested against real field cases, the tool produced positive indications of its potential as failure predictor. However, it did not distinguish the correct failure sufficiently clearly. Further development and refinement of the tool is necessary
- The next version of the ontology must include:
  - Bottom-up testing on many failure cases
  - Expand and improve symptoms
  - Short lasting symptoms must be equipped with decay characteristics
Acknowledgement
Two master students, Daniel Rosland and Andreas Årstad, did the programming and testing. They were limited to 21 weeks totally for research and for writing the thesis.

Nomenclature

<table>
<thead>
<tr>
<th>Symbols</th>
<th></th>
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</thead>
<tbody>
<tr>
<td>BPOS</td>
<td>m</td>
</tr>
<tr>
<td>c</td>
<td></td>
</tr>
<tr>
<td>d</td>
<td>m</td>
</tr>
<tr>
<td>DMEA</td>
<td>m</td>
</tr>
<tr>
<td>ECD</td>
<td>kg/l</td>
</tr>
<tr>
<td>HKL</td>
<td>N</td>
</tr>
<tr>
<td>L</td>
<td>m</td>
</tr>
<tr>
<td>M</td>
<td></td>
</tr>
<tr>
<td>MFI</td>
<td>l/min</td>
</tr>
<tr>
<td>n</td>
<td></td>
</tr>
<tr>
<td>p</td>
<td>Pa</td>
</tr>
<tr>
<td>q</td>
<td>m³/s</td>
</tr>
<tr>
<td>SPP</td>
<td>Pa</td>
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<td>t</td>
<td>s</td>
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<tr>
<td>Δ</td>
<td></td>
</tr>
</tbody>
</table>

Abbreviations.
CS Casing shoe
Csg Casing
D Diameter
DS Drill string
EoW End of well (report)
Fm Formation (sedimentary)
LC Lost Circulation
SGF Shallow Gas Flow
MWD Measurements While Drilling

References


