Experience transfer for process improvement

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A B S T R A C T

The oil well drilling process is the selected representative of a challenging industrial process. The drilling process is becoming more complex as oil fields mature and technology evolves. At the same time, the amount of information is increasing in volume and frequency. Although technology is advancing, failures occur at almost the same rate as before, leading to loss of valuable time. Whenever the process is failing, or running smoothly, valuable experience is gained. To take advantage of established and continually growing new experience a formalized methodology, knowledge intensive case-based reasoning, was applied for capturing of drilling process experience and for reusing it. Experience was collected from different information sources. Structured cases were used to describe failure episodes; its circumstances and how the failure was repaired. A general domain knowledge model supports the case-based reasoning process. It was demonstrated how the system was able to recommend how to solve problems when they arise, while at the same time bridging the gap between new and experienced personnel. Method performance was tested on 62 selected field cases. The system also identified the failure causes of problems and could thereby suggest more effective repair actions.

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1. Introduction

A majority of the remaining oil and gas resources are located inside the continental shelves. Offshore drilling operations are very expensive, and numbers of wells are kept as low as possible. For this reason offshore wells tend to be long and complex. This is also the explanation of why the number of process failures does not diminish much over time. In spite of technology evolution, complexity also increases.

A failure during drilling operations is defined as the state of a process when non-productive time (NPT) is occurring. NPT is typically in the range of 15% of total rig time, but can become much higher during drilling of difficult wells (Halliburton Solving Challenge, 2012). The motivation behind the work presented here is to advance computerized methods for helping the petroleum industry in reducing unwanted downtime.

Another worry in the industry which supports our motivation is the knowledge gap created by “The Great Crew Change” that exists in most companies (e.g., (McCormack, 2010)). The problem is not one of just filling the gaps. There are sufficient numbers of people entering the workforce to do that. The problem is one of “experience attrition”. The immediate challenge is therefore how to transmit the soft and hard skills necessary to quickly bridge the gaps between new and existing personnel. Companies want a measurable return on investment. They want to achieve a reduction in accidents, an improvement in oil and gas measurement yield, and fewer lost days of production.

The ultimate goal of our research is to improve process quality and efficiency by systematically capturing useful human experience during a drilling process and make relevant past experience available on-line when needed.

This calls for skills to be transportable between companies and among different industries. Case-based Reasoning (CBR) is a methodology that enables computer systems to assist in achieving these tasks. The goal of the work described in this paper is to investigate how knowledge transfer in the drilling process can effectively be realized by combining the re-use of situation-specific experiences (cases) with justifications and explanations generated by a general domain model (ontology). The combined approach is referred to as knowledge-intensive CBR. We have developed an experimental system that is able to read data from a drilling process and capture interesting parts of it (Aamodt et al., 2012). After having captured and stored human experience accompanied by technical information, we demonstrate different ways of re-using the experience, and point out especially two applications in larger detail:

• Determine the optimal repair of a problem
• Determine the failure cause of a problem
We have studied a novel combination of two technologies that have proved to work well in other industries: Case-based reasoning (Cheetham and Watson, 2005) and Ontologies (Obrst et al., 2003). This combination has also been applied to other problems in the oil and gas domain (Kravis and Irgang, 2005).

Case-based reasoning is a method and a technology for solving new problems in complex processes by comparing a new problem to previous situations, and reusing the experience from the most similar situations in solving the new problem (Aamodt and Plaza, 1994). CBR can be described as adoption of common human problem-solving behavior for computer use (Popa et al., 2008). In practical systems, the technology incorporates different types of information, which empower the system to learn and adapt from an ever-growing case base of new experiences. In order to set our method in a wider perspective, in Section 2 we discuss existing approaches to experience transfer.

In Section 3 follows a description of how the case knowledge and general knowledge are represented, and the various sources of information and knowledge are described. The quality of the CBR systems, in terms of finding relevant past cases, has been tested on field data in a small scale, and the results are presented in Section 4, including two applications. A discussion of the results and future plans concludes the paper.

2. Related research

Technology itself is advancing at an impressive rate, introducing methods to solve new and old problems more efficiently. To learn from mistakes while applying new or old technology brings technology faster forward. To take advantage of this proven fact the industry has turned to AI-engineers, realizing that experience transfer is an AI challenge.

The transfer of knowledge according to the CBR paradigm involves three main processes: observing and interpreting a situation, identifying and capturing interesting information in the situation for integration into the knowledge base (i.e. the case base), and finally searching for and re-using past cases as knowledge in new situations. In general, episodic experience from drilling operations is either stored in writing, e.g. as different types of drilling reports, or as human experience in the heads of the people involved in the operations. Experiences typically contain the drilling operators’ understanding of the process; how they handled the situation; their ability to point at root causes, etc.

In-depth studies to identify and share successful drilling practices across companies (Brett et al., 1998) have shown measured benefits in the order of 10%. Thorsvoll and Grotmol (1999) reported a similar approach; joint business development between operator and service companies’ added value to both parties after a systematic approach to improve quality and communication (experience transfer). Integrated operations represent a recent method of experience transfer (Miller et al., 2006). Real-time data transferred from offshore to land enable support of drilling operations in an efficient manner. Support from onshore results in a much better utilization of engineering resources and experience.

A more recent example is the blow out in the Gulf of Mexico from Deepwater Horizon (BP, 2010). A thorough investigation made it rather clear that both the cement operation and cementing equipment failed due to poor design and risk assessment.

A particular challenge in computerized experience transfer systems is the knowledge representation issue, i.e. how to represent the symbol structures that stand for human experience in formal data structures in a computer. CBR applications are still at its beginning in the oil industry, although CBR itself is a well-established technology. Previous work within the oil industry related to how experience is organized and represented to make it fit for reuse can be divided into (1) situation-specific approaches, and (2) generalized approaches.

In situation-specific approaches case-based reasoning is the dominating technology. Experience is represented as a collection of parameters and other information that together describe an episode, i.e. an interesting situation worth remembering. Typically, cases are clustered into classes with the same solution. The CBR task is to match a new case with historical cases and assign the class of the best matched case(s) as the correct class of the new case. Previous work on applying case-based and model-based (ontology-based) reasoning to oil and gas-related problems includes Mendes et al. (2003), Abdollahi et al. (2008), Popa et al. (2008). Earlier work by the authors includes initial investigations of the technology’s potential (Nordha et al., 1992), results from the EU project Noemie on combined decision-support and data mining (Skalle et al., 2000) decision support by first finding the root cause of the problem (Shokouhi and Skalle, 2009; Shokouhi et al., 2009), earlier report on experience transfer (Skalle et al., 2010), a survey of CBR applications in drilling engineering (Shokouhi et al., 2012), and a description of Verdande Technology’s DrillEdge system (Gundersen et al., 2013). While most of this research focus on the CBR methods, the work presented here has a stronger emphasis on the role of the general domain model, i.e. the ontology.

Research at the Australian Research institute (SCRI) documented one of the first applications of CBR in the petroleum engineering domain (Kravis and Irgang, 2005). Alternate drilling plans were derived from comparison with previously drilled wells. Each well represented one case. Bhushan and Hopkinson (2002) applied CBR to globally search for reservoir analogues as an important step in planning and development of oil fields. Such information would be useful when appraisal information is limited. The key lies in characterizing each reservoir by a set of attributes which describes the reservoir and can be used to differentiate it from other reservoirs.

Khajotia and colleagues (2007) took a non-typical approach in applying CBR within a predictive mathematical model. The method was designed to mimic the approach to the problem taken by experienced field personnel, by taking knowledge of corrosion rates from existing cases and apply them in new fields having somewhat similar parameters.

In generalized approaches to experience transfer, rule-based reasoning is the typical method. A rule, whether a final decision rule or an intermediate inference step, can be viewed as a generalization over a set of cases that share many of the same properties. Rules are empirical and may be based on sound, if not well understood, physical, economic, social, or other principles (Brown et al., 2005). They allow us to shortcut some thinking processes and, in doing so, can also cause us to make costly mistakes. As we grow more and more experienced, we personally develop and adopt new rules of thumb. But rules often have exceptions. In a rule-based setting, cases can be viewed as exceptions to the rules, opening up for combined systems.

In model-based reasoning knowledge is represented as multi-relational dependencies between parameters and other concepts, as opposed to the single relation (i.e. the “if-then” implication) of rule-based methods. In the knowledge-intensive CBR approach taken in our research, model-based reasoning – based on an ontology model – constitutes the generalization-based method.

3. Our approach to experience transfer in the drilling process

In our approach to knowledge-intensive CBR the case base and the general domain knowledge play together in helping the user identify possible problems of an ongoing drilling operation. The structure and contents of these knowledge types are as follows.
In CBR, a specific situation that is occurring or has occurred before is referred to as a case. The parameter data and other information that constitutes a case need to be represented in an appropriate case structure. The set of cases contained in a system is called its case base. In some CBR systems all the knowledge possessed by a system is contained in the case base. In the method presented here additional knowledge in the form of general domain relationships between significant oil drilling concepts constitutes an additional type of knowledge in the system. This part of the knowledge base may be viewed as an ontology, and principles of ‘ontology engineering’ (Staab and Studer, 2009) have been adopted, through which the knowledge has been structured and interrelated in a logical manner.

3.1. Storing of experience

The problem type we have selected to exemplify experience is restrictions in the wellbore. Fig. 1 demonstrates a drilling situation and defines the engineering terms. It is experienced during tripping operations (hoisting or lowering the drill string) and may escalate to failures. Persistent reoccurrence of such problems calls for a reaming (enlarging wellbore diameter) activity to hinder the restriction to escalate into stuck pipe and lost circulation. Wellbore restrictions represent a sufficiently complex problem and were selected as the test application.

We learned in Section 2 that there are a large variety of ways to organize and transfer experience; through well plans (Bhushan and Hopkinson, 2002), mathematical models (Khajotia et al., 2007), etc. Our approach has been to build structured cases in order to describe the problem in a purposeful manner. A case contains several types of experience, and it is structured to help facilitate the knowledge and the experience that stem from users. Fig. 2 illustrates the structure of a case, divided into three sections, three sections which are dictated by three corresponding requirements:

1. The need of case indexes for retrieval and similarity assessment:
   All information embedded in the cases, before triggering of the case which characterizes the episodes, are used to discriminate between cases (similarity assessment).
2. The selected repair method:
   The actions taken after the case was triggered – best practice repair.
3. The result after repair:
   Outcome of repair and gained experience. Can an improved repair method be recommended?

Whenever a new problem situation is in progress, a warning is triggered when the situation is sufficiently similar to previous situations (stored cases in the case base). New cases are initially

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**Fig. 1.** A typical drilling operation. It starts off in the vertical direction but deviates often in an almost complete horizontal direction. Here restrictions are bound to occur during the different process activities unless signs of restrictions are detected and properly tended to.

**Fig. 2.** The case structure of our system.

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Some definitions:
- Tripping = hoist or lower drill string
- Reaming = cleaning hole by rotating/moving drill string
- Stuck pipe = drill pipe cannot pass a restriction
- Lost circulation = part of drilling fluid lost to fractures in the well
composed of items shown in Fig. 2, upper section. The data contain indicators and statistics of the real time drilling parameters, including interpreted events and type of activity on the rig. These are needed as symptoms of the state of the drilling process.

After the situation is repaired and restored, the completed case contains additional description of the problem and how the case was triggered and resolved. The middle case section contains direct experience or information. It describes how the involved personnel handled the episode and what was learned. It contains statistics on time spent on well cleaning, repair actions, outcome of the repair, groups of classes (classes are used to evaluate matching ability) and lesson learned.

Outcome is a measure of what effect the recommended repair action had. Was it successful, or could the recommended repair job be even better performed? E.g.: After completing the specific well section, a steel casing is routinely installed and cemented in place. Loss of time during casing installment and cementing operations caused by wellbore cleaning related problems is a poor outcome. In this case, one could state that the repair action, hole cleaning, which was done poorly, was far from optimal, as it lead to loss of time during casing and cementing.

A very useful property of a CBR system is its ability to capture and store a problem just solved as a new case. Case building is a process which utilizes principles of knowledge engineering. Fig. 3 exemplifies the process of identifying case elements through the identification of relevant information that describes an episode.

3.2. Knowledge modeling; a means of support during re-use of experience

The purpose of the ontology is to serve as a knowledge model for model-based reasoning to assist the CBR process. The ontology can be viewed as a semantic network, where each node in the network corresponds to a concept in the knowledge model, and each link corresponds to a relation between concepts. A concept may be a general definitional or prototypical concept, and may describe knowledge of domain objects as well as problem solving methods and strategies. A network view to concept definition is taken, in which each concept is defined by its relations to other concepts. Fig. 4 illustrates the three main types of knowledge in the model: a top-level ontology of generic domain-independent concepts, a middle-level ontology of domain-specific knowledge, and a bottom-level that constitutes instances, i.e. cases. Data from the real world environment enter into cases – possibly after some transformation or abstraction. Cases are linked into the ontology model by the fact that each parameter in a case is represented as a concept in the ontology.

Ontology is a term used in philosophy, encompassing the study of what it is. The application of Ontology within Information Technology and Engineering is more recent, and has replaced and enhanced terms like knowledge model, data model, term-catalogue, etc. All ontologies make some assumptions about the world that they represent. In our ontology, 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 basically two subclasses: Entity (objects in the real world), and Relation (bi-directional relations between entities). In addition a third subclass is introduced, Descriptive Thing, which is a syntactical or structural description of the entities. An example is Case Structure. Fig. 5 illustrates a part of the ontology. Only class-subclass relations are shown in the figure. For example, the leftmost concept State is a subclass of Entity. Our approach is based on the Creek System (Aamodt, 1992, 1993) and later re-implementation and extensions of that system (Aamodt, 2004).

Over the last years an extensive ontology of oil and gas terms has been developed within the international community, and also made into a standard, the ISO 15926 (http://15926.org/). Our model set out to define drilling engineering terms in accordance with the international standard ISO 15926 whenever practically feasible. Unfortunately that turned out to be quite difficult, partly because drilling terms are not well developed in ISO15926. The result is that our current ontology differs substantially from that standard. In our ontology’s middle layer all petroleum related information used in the reasoning process are formally defined entities, e.g. the activity of pulling the drill string up the well is given the entity name Tripping Out.

To enable reasoning, symbols are connected through relations that facilitate default inference as well as different types of property inheritance. Examples of relationships are:

- Swelling Clay may lead to Improperly Cleaned Well
- Pack Off is caused sometimes by Poor Hole Cleaning
- Pack Off is caused occasionally by Swelling Clay

Such relationships will assist in pointing out the failure cause.

3.3. Sources of experience

A case is the basis for reasoning and all relevant information is contained in it. Fig. 6 indicates two basic sources of experience:

1) On-line interpretation of drilling data. We have developed a system for on-line interpretation of drilling data (Verdande Technology, 2009; Aamodt et al., 2012; Gundersen et al., 2013). The work presented here differs from that system in its primary focus on utilizing the ontology knowledge to reveal failure causes.

Surface and downhole data, shown to the left in Fig. 6, are logged typically every 5th second. These data are continuously evaluated and interpreted. Data indicating abnormal behavior
are transformed into symptoms in the form of Interpreted Events, Inferred Parameters or Indicators, data types that are important for indexing and similarity matching of cases. Symptoms show up through signs such as tight spot, packing-off, hard strings, etc. Indicators are mathematical functions for estimating, e.g. chemical stability of the geological formation. Inferred parameters are logical groups of parameters, e.g. TVD/MD, MW-Pore Pressure. We would like to state that our method is depending on symptoms. If symptoms are available from other sources we utilize them, however, we found that in most cases we had to formulate the symptoms ourselves.

(2) Experience stored in documents. A case needs context data referred to as static and semi static data. These are found in drilling operation logs and documents. An expert retrieves types of information which may characterize a case such as geometry of the well and equipment, lithology, history of the operation both in a time and depth view, helping us to focus the on-line interpretation, etc. Knowledge is thus being extracted from discrete information sources in client databases. New cases which are generated in a live process obtain information from the same two information sources. Retrieved cases are undergoing a quality assurance process.

4. Testing of method

In this chapter we demonstrate first the number and type of cases which were generated from a large amount of historical data, then how useful knowledge was retrieved from the cases.

Wellbore restriction is our initial target problem. The problem is experienced during tripping operations and may escalate to Tool Weight (wellbore path), Took Weight (wellbore restrictions take part of the drill sting weight), High Torque or High Drag. Reoccurrence of such signs calls for reaming activity to hinder the restriction to escalate into Stuck Pipe and Lost Circulation.

4.1. Collecting field data

Seven different wellbore sections drilled in an offshore oil field during 2004–2006 were studied, resulting in 62 cases of wellbore cleaning episodes. Most of the problem cases were located in the bottom part of the wells since this part is more horizontal than the very upper part. This is demonstrated in Table 1.

We grouped the cases into different classes for the purpose of testing our method against potential target classes:

<table>
<thead>
<tr>
<th>Failure Type</th>
<th>Repair Time</th>
<th>Consequence</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In our study we investigated only one failure type: Improperly Cleaned Well. This failure type may be caused by two error types; Reactive Fm (Fm=formation, one of the few abbreviations we allow in the knowledge model) and Accumulated Solids, as demonstrated in Table 2. To determine downhole failure/error types on the basis of surface observations turned out to be very difficult. We had only weak indications that most of the errors/failures belonged to Accumulated Solids, while in a few cases we saw signs pointing to Reactive Fm. The error distribution is therefore not presented in Table 2.

Repair Time was easier to deal with since we could measure it accurately. We defined four sub-classes as shown in Table 3. This was the selected target class for further testing. Consequence refers to the additional time it took to repair problems encountered during subsequent casing running and cementing operations in the same well. Table 4 defines four subclasses and the distribution among the 62 cases.

4.2. Selecting the correct case class

Repair Time was selected since it represents a defined and measurable distribution. A test of the implemented system was undertaken in order to evaluate its ability to select cases from the right solution class. A standard testing algorithm (leave-one-out cross-validation) was used.

Table 2

<table>
<thead>
<tr>
<th>Error group</th>
<th>Subclass</th>
<th>Subclass</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reactive Fm</td>
<td>Enlarged wellbore</td>
<td>Erosion of weakened wellbore</td>
</tr>
<tr>
<td></td>
<td>Dissolving limestone</td>
<td>Swelling clay</td>
</tr>
<tr>
<td></td>
<td>Reactive shale</td>
<td>Sloughing shale</td>
</tr>
<tr>
<td>Accumulated solids</td>
<td>Increasing filtercake</td>
<td>Chunks in wellbore</td>
</tr>
<tr>
<td></td>
<td>Solids settling</td>
<td>Accumulated cuttings</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Barite sag</td>
</tr>
</tbody>
</table>

Table 3

<table>
<thead>
<tr>
<th>Class</th>
<th>Class name</th>
<th>Class definition (NPT: hours)</th>
<th>Frequency (occurrences)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Insignificant repair time</td>
<td>&lt; 1 h</td>
<td>29</td>
</tr>
<tr>
<td>2</td>
<td>Short repair time</td>
<td>1–3 h</td>
<td>11</td>
</tr>
<tr>
<td>3</td>
<td>Long repair time</td>
<td>3–15 h</td>
<td>17</td>
</tr>
<tr>
<td>4</td>
<td>Gave up well</td>
<td>&gt; 15 h</td>
<td>5</td>
</tr>
</tbody>
</table>

Table 4

<table>
<thead>
<tr>
<th>Class</th>
<th>Class Name</th>
<th>Class Definition (extra spent time during completion - days)</th>
<th>Frequency (number)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Insignificant consequence</td>
<td>&lt; 1 h</td>
<td>38</td>
</tr>
<tr>
<td>2</td>
<td>Low consequence</td>
<td>1–3 h</td>
<td>13</td>
</tr>
<tr>
<td>3</td>
<td>High consequence</td>
<td>3–15 h</td>
<td>7</td>
</tr>
<tr>
<td>4</td>
<td>Gave up well</td>
<td>&gt; 15 h</td>
<td>4</td>
</tr>
</tbody>
</table>
The test was performed in a stepwise fashion. First, all 62 cases were tested against manually analyzed and tagged events, then against automatically generated triggering events, and finally against completely new logs. Manual tests implied that cases were defined and tagged (marked) manually in the real-time log. Testing of the 62 cases against manually tagged triggering events resulted in acceptable and close to excellent test results. However, many of the 62 triggering events were not "seen" by the automatically performed test. We introduced several modifications in the preparation of the next test round:

- We allowed only cases which could be automatically detected through on-line interpretation.
- Due to a low number of cases, they were grouped into only two classes; Class A contained Insignificant and Short Repair Time, Class B Long Repair Time and Gave Up Well.
- Cases which had repair time shorter than 0.1 h (6 min) were excluded.

These requirements reduced the number of cases to 22. The matching-test gave as a result that class A cases were retrieved correctly in 82% and class B in 73% of the time. The baseline percentage, representing the probabilities of wild guesses according to the data distribution, was approximately 50% for each class. All together the test clearly indicates the feasibility of the method, but not as well as hoped for.

4.3. Identifying the failure cause by means of the knowledge model

Due to unsatisfactory results in the CBR test above, an alternative test was designed, trying to reveal the failure cause through the knowledge model.

In step 1 the observations in the selected failure case were embedded into the knowledge model as discussed in Section 3.1. Observations, error and failure causes are related in the ontology through intermediate concepts, along cause–effect chains. Fig. 7 illustrates all the potential errors in the wellbore. From Fig. 7 we picked out the two error types which most often are related to the failure Improperly Cleaned Well, and summarized their error subclasses in Table 2. This statement will be demonstrated below. In this paper we have specified failure causes through the name of the failure. By pointing out the failure/error subclasses the failure cause is determined. Error/failure cause and error/failure type are synonyms in this paper.

Case WF023 was selected for demonstrating the methodology. The relevant observations were picked out (relevant for differentiating between error types):

- Low Mud Viscosity
- Very Long Open Hole Time
- Pack Off
- Took Weight
- Low ROP
- Increasing Drag
- Low Well Inclination

In Fig. 8 the observations (circled) are imbedded in the knowledge model. Internal relationships are relating them to potential errors/failures. There is a path from all the observations either directly or indirectly to two different root causes; Swelling Clay and Cuttings Accumulation. The strength of the paths is the product of the strength of each relation leading from the observation to the target entity:

\[
\text{Path strength} = \prod_{i=1}^{n} \text{relation strength}_i
\]

where \( n \) is the number of serial relations. For example, the path; Low Mud Viscosity leads to (0.7) Solids Settling sometimes causes (0.6) Accumulated Cuttings results in path strength of 0.7*0.6=0.42. All results are presented in Table 5. The longer the path the weaker it becomes. All possible paths leading to the failure Improperly Cleaned Well are included. Other failures were also "hit", but at a far weaker strength, and they were all omitted to clarify our methodology of cause determination.

The total explanation strength for each target entity is determined by adding all paths leading to the specific target error as shown in Table 5. It shows that the probability of the only two activated causes is:

- Accumulated Cuttings: 62%
- Swelling Clay: 38%

To know the failure cause is really valuable as discussed in the next section. And it will strengthen the case selection process in Section 4.2 above.
5. Discussion

Given that a past case stored in the case base was found to contain valuable knowledge, this matching case can be used to inform the user about:

- How the well should be repaired
- Time needed to clean (the most) similar wells
- Can repair be performed alternatively?
- Potential future problems, for example during the later casing operations

Correct diagnosis of the problem will lead to treatment that is appropriate and will result in efficient repair actions, leading to significant cost reductions.

The assumption is that treatment of historical cases of best matching classes also is suitable for new cases of this class. We claim this is a fair assumption since 82% of all the selected cases, when later evaluated, were classified as sufficiently similar to this class.

However, since the downhole cause of the problem is normally not 100% known, the repair action is not necessarily directly related to the cause. It is for this reason difficult to improve the repair efficiency. The operator will naturally select repair methods which are commonly in use to treat hole-cleaning problems, but which are not necessarily well suited for that specific type of root cause since stated cause may be wrong.

The solution and/or the repair applied in historical cases, e.g. case WF023, must be checked whether it corresponds with recommended actions for the specific situation. After an incident has taken place, the user tries out a repair strategy. After the outcome of the selected repair action becomes known, the repair strategy can be evaluated. Did it work? Experts are consulted through interviews or through investigations. If case WF023 worked well the case would be accepted as a trustworthy case and kept in the data base. If the evaluation was not included in the process, the tool would become static and some cases could result in a poor repair method being recommended.

We have exemplified the utilization of a CBR system directed towards reduction of downtime. When run in the field, the user will test the recommendations from the system in a real setting. After evaluating the outcome of recommended repair actions and eventually adjusting the cases, the user should gradually be witnessing improved outcome and more precise recommendations.

Improvements are pending; new indicators; new events; higher quality of existing events will improve the tool. Access to

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**Table 5**

Result after testing case WF023 by means of the knowledge model.

<table>
<thead>
<tr>
<th>Observation</th>
<th>Path strength</th>
<th>Explanation strength</th>
<th>Target error</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pack off</td>
<td>0.7 / 0.5–0.35</td>
<td>2.97</td>
<td>Accumulated cuttings</td>
<td>2.97/4.67–0.62</td>
</tr>
<tr>
<td>Took weight</td>
<td>0.5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Increasing drag</td>
<td>0.7</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low ROP</td>
<td>0.4 / 0.5–0.2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low mud visc.</td>
<td>0.7 / 0.6–0.42</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low well incl.</td>
<td>0.7</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pack off</td>
<td>0.4</td>
<td>1.80</td>
<td>Swelling clay</td>
<td>2.97/4.67–0.38</td>
</tr>
<tr>
<td>Took weight</td>
<td>0.6</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Very long open H.</td>
<td>0.8</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>4.67</td>
<td></td>
<td></td>
<td>1.00</td>
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**Fig. 8.** Relevant observations (circled) from Case WF023 are activated during the episode, pointing to two errors. Accumulated Cuttings and Swelling Clay point with different explanation strength to the failure Improperly Cleaned Well. Only relevant observations and relevant concepts are shown. The arrows represent many different relation types, e.g. 'causes sometimes' and 'has subclass'.

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a sufficient amount of data of sufficiently good quality and sampling rate has been problematic. More data will be needed in order to perform a more elaborate evaluation. The more paths and the better we can differentiate between errors/failures. All improvements will allow similar episodes to become more similar. They will open for formal and reliable prediction of failure cause. In the real process, up to now, good engineering judgment determines failure cause. The correct cause will improve quality of advises. Research is continuing on refining the system in response to industry feedback.

After the results reported here, Verdande Technology has – as earlier mentioned – developed and extensively tested a commercial and customer-targeted CBR system that utilizes many of the design principles of the reported system. That system, named DrillEdge, has a stronger focus on combined data analysis and case-based reasoning than the experiment reported here. It has shown excellent accuracy and performance properties in real drilling settings as reported by several of their customers (www.verdandetechnology.com). The system received the 2011 Special Meritorious Awards for Engineering Innovation, category Intelligent Systems and Components (http://www.epmag.com/mea/mea.winners.php).

6. Conclusion

An on-line software tool has been developed and evaluated on the basis of historical real-time drilling data. The results are promising. The system has the capability of recognizing episodes and relating them to situations that have occurred before. The episodes are stored as cases consisting of three separate parts: circumstantial information and gained experience, explanation of why the situation arose and how it was handled, and the outcome of the action taken.

- Experience embodied in a case is retrieved not only from data streams and documents, but also from the user and other experts during case generation, ontology building, and case evaluation.
- Cases representing complex domains like oil well drilling operations need to be related to a rich ontology since the case space is small. Concept expressing experience is translated into a symbolic language and then stored in the ontology as interrelated entities.
- Initial real-time runs have proven the tool’s functionality and pointed out potential user support. Tests have showed that the CBR system matched and retrieved cases of the correct class to an acceptable degree, even with the sparse data available for the experiments. Applying the knowledge model is an alternative method of revealing the correct failure cause. This will improve the CBR-method and enhance the quality of advises given.

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