Advances in Drilling Technology - E-proceedings of the First International Conference on Drilling Technology (ICDT - 2010) and National Workshop on Manpower Development in Petroleum Engineering (NWMDPE - 2010), November 18-21, 2010.
ISBN: 978-93-80689-03-6,

Transfer of experience for improved oil well drilling

Pål Skalle, Agnar Aamodt and Odd Erik Gundersen
Norwegian University of Science and Technology, NTNU, Norway

ABSTRACT

The drilling process is getting increasingly 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 do occur, leading to loss of valuable time. When ever the process is running smoothly or is failing, valuable experience is gained. However, experience attrition is a well-documented problem. To take advantage of established and continually growing new experience a formalized methodology, case-based reasoning, was applied in a decision support system for capture and reuse of drilling operators' experience. A case describes an episode during drilling, its circumstances and method to repair the problem. A general domain knowledge model, an ontology, supports the case-based process. In this paper we focus on how experience can be captured and transferred from different information sources and then stored in cases. It was demonstrated how the system was able to recommend how problems can be solved when they arise, while at the same time bridging the gap between new and experienced personnel. The quality of selecting the most relevant experience was proven through performance testing of 62 field cases. The system was used to identify root causes of problems that had happened as well as to suggest repair actions.

KEYWORDS: Oil well drilling, experience transfer, ontology, drilling failure, downtime, case-based reasoning, symptoms

INTRODUCTION

The motivation behind the work presented here is to advance computerized methods for helping the petroleum industry in reducing unwanted downtime. 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 (e.g. (Obrst, Liu and Wray, 2003), and have recently been applied to the oil&gas domain (Kravis and Irrgang, 2005).

Case-based reasoning (CBR) is a method and a technology for solving new problems in complex processes by comparing them to previous situations, and reusing the experience from the most similar situations in solving the new problems (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 empowers the system to learn and adapt from an ever-growing case base of new experiences. 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.

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 method the knowledge has been structured and interrelated in a logical manner. The knowledge gap created by "The Great Crew Change" that exists in most companies has been well documented and discussed (e.g. (Mc Cormack, 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 transmitting the soft and hard skills necessary to quickly bridge the gaps between new and existing personnel. Productivity is an ongoing training concern. Today, training is moving closer to sites of operations – a trend that will only increase as the number of new entrants to the industry increases. At the end of the day, 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. That means skills that are transportable between companies and among different industries. CBR is a methodology that enable computer systems to assist in achieving all these tasks.

The goal of the work described in this paper is to investigate how knowledge transfer in drilling 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 a "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. 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:

1. Determine the root cause of a problem
2. Determine the optimal repair of a problem

The next chapter discusses some approaches to experience transfer, in order to set our method in a wider perspective. This is followed in chapter 3 by a description of how the case knowledge and general knowledge are represented, while chapter 4 describes the various sources of information and knowledge. The quality of the CBR systems, in terms of finding relevant past cases, has been tested on a small scale, and the results are presented in chapter 5. In chapter 6 the above two application foci (identifying root cause and suggesting repair action) are outlined, including the way the case-base and the ontology are combined to achieve the results. A discussion of the results and future plans concludes the paper.

EXPERIENCE TRANSFER

The transfer of knowledge in the CBR paradigm involves three main processes: observing and interpreting a situation, identifying and capturing interesting information in the situation, and searching for and re-using it as knowledge in new situations. 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) resulted in benefits on 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 appoarach to improve quality and communication (experience transfer). Integrated operations represent a resent method of experience transfer (Milter et.al. 2005). Real time data transferred from offshore to land enables support of drilling operations in an efficient manner. Support from onshore results in a much better utilization of engineering resources and experience.

Few safety-related incidents over the past twenty years have been noticed by so many people worldwide as the loss of the Space Shuttle Challenger in 1986, the crash of Air France's Concorde in 2000, and the loss of the Space Shuttle Columbia, 2003 (Gordon, 2006). Any piece of information, observation, referred to as "deviance of normalization" was used to find the root cause. 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 used, as already mentioned. Experience is represented as a collection of parameters and other information that describes an episode, i.e. an interesting situation. Typically, cases are clustered into classes with the same solution. The CBR task is to match new cases with historical cases by retrieving them from the correct class. Previous work include Mendes et al (2003), Abdollahi et al (2008), Popa et al (2008), in addition to earlier work by the authors.

SCIRO documented one of the first applications of CBR in the petroleum engineering domain (Karvis and Irrgang, 2005). Alternate drilling plans were derived from comparison with previously drilled wells. Each well represented one case. Bhushan at al. (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 describe the reservoir and can be used to differentiate it from other reservoirs. Khajotia and colleagues (Khajotia et. al., 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. whether general or specific. 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.

EXPERIENCE AND GENERALIZED KNOWLEDGE

In our approach to knowledge-intensive CBR the case base and the general domain knowledge play together in helping the user identify possible problem of an ongoing drilling operation. The structure and contents of these knowledge types are as follows.

Case structure and experience content

The problem type we study is *restriction in the wellbore*. It is experienced during tripping operations and may escalate to failures. Persistent reoccurrence of such problems calls for reaming activity to hinder the restriction to escalate into stuck-pipe and lost circulation. Since wellbore restrictions represent a complex problem it was selected as our first test application.

We learned in the previous chapter that there is a large variety of ways to organize and transfer experience; through mathematical models, through well plans 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 stems from users. Three common requirements dictate case structure:

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

Figure 1 illustrates the structure of a case, divided into three sections as described above.

Case retrieval info BToC is composed of items shown in Figure 1, upper section. The data contains 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. Finally it contains description of the problem and how the case was triggered. The middle case section contains direct experience or case re-use information AToC. It describes how the personnel involved 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); lesson learned; Outcome is a measure of what effect the recommended repair action had. This is useful information the next time the drill string and its Bottom Hole Assembly is passing by the problematic part of the well where the case episode took place. For example: 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 repair was not optimal one could state. A very useful property of a CBR system is its ability to capture and store a problem just solved as a new case. However, an initial case base is typically constructed by manual means, utilizing principles of knowledge engineering. Figure 2 exemplifies the process of filling the case structure with contents through the identification of relevant info that describes an episode.

Ontology structure and content

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. Figure 3 illustrates the three main types of knowledge in the model: a top-level ontology of generic, domain-independent concepts, middle-level ontology of the domain-specific knowledge, and a bottom-level that constitutes instances, i.e. cases. Data from the real world environment enters into cases – possibly after some transformation or abstraction. Cases are linked into the ontology model by the fact that each parameter that describes a case is represented as a concept in the ontology.

Ontology is a term used in philosophy, encompassing the study of what is. The application of Ontology within Information Technology and Engineering is more resent, and has replaced and enhanced terms like knowledge model, data model, term-catalogue etc. All ontologies make some assumptions about the world that it represents. 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 three subclasses; Entities (objects in the real world), Descriptive Things (description of Entities) and Relations (bi-directional relations between subclasses and instances). Figure 4 illustrates a part of the ontology. Only class-subclass relations are shown in the figure. The leftmost concept, State, is a subclass of Entity. Over the last years an extensive ontology of oil and gas terms has been developed, and also made into a standard, the ISO 15926 (Batres et. Al, 2007). Our model sets 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, with the result that our ontology differs substantially from that standard. In our ontology's middle layer all petroleum related information used in the reasoning process is 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 may lead to wellbore enlargement after long exposure time
> Enlarged wellbore sometimes cases tight spots in horizontal wellbores

Such relationships will assist in pointing out the root cause and / or in explaining the episodes. More on that in chapter 6.

SOURCES OF EXPERIENCE

A case is the basis for reasoning and all relevant information must be gathered. Figure 5 indicates two basic sources of experience:

On-line interpretation of drilling data. We have developed a system for on-line interpretation of drilling data (Verdande, 2009). Surface and downhole data are logged typically every 5th second. These data are continuously evaluated and interpreted. Anomalic behavior is transferred into either Interpreted Events, Inferred Parameters or Indicators, data types that are important for indexing and similarity matching of cases. Events show up through signs such as tight spot, packing-off, hard stringers etc. Indicators are mathematical functions for estimating, e.g. formation chemical stability. Inferred parameters are logical groups of parameters, e.g. TVD/MD, MW-Pore Pressure. Interpreted drilling data are necessary in order to improve the understanding of downhole processes and enable us to find the causes of hole restrictions.

Experience stored in documents. An expert performs an initial investigation of drilling operation logs and documents and retrieves information which may characterize a case such as lithology, history of the operation both in a time and depth view, etc. Drilling engineers rarely have time to analyze the entire dataset before making recommendations. And since access to oil industry experts for the purpose of knowledge acquisition is limited, knowledge is being extracted from discrete information sources in client databases.

IDENTIFYING THE CORRECT SOLUTION CLASS - TEST RESULT

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 (cross-validation) was used. Seven different wellbore sections drilled in an offshore oil field during 2004 – 2006 were studied, resulting in 62 cases of wellbore cleaning episodes. Three groups of solution classes were defined as potential target classes:

Root Cause
Repair Time
Consequence

Root Cause represents the ultimate test. However, we had insufficient knowledge (real time data interpretation) of the downhole processes to be able to reveal downhole root cause with high enough probability . Of the two remaining classes, Repair Time represents a defined and measurable quantity and was therefore selected. Consequence refer to the additional time it took to repair problems encountered during subsequent casing running and cementing operations in the same well. Repair Time has four sub-classes:

Class 1: Insignificant Repair Time	< 1 hour
Class 2: Short Repair Time	1-3 hour
Class 3: Long Repair Time	3-15 hour
Class 4: Gave Up Well	> 15 hour

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 if not excellent test results. However, many of the 62 triggering events were not "seen" by the automatically performed test. We introduced several modifications in preparation of the next test round:

- We allowed only cases which could be automatically detected through on-line interpretation
- Due to 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 minutes) were excluded

These requirements reduced the number of cases to 22. The matching-test gave as result that class A cases were retrieved correctly in 82 % and class B in 73 % of the time. The baseline percentage was approximately 50 % for each class. All together the test results strongly indicates the feasibility of the method. Access to 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.

TWO APPLICATIONS OF THE GAINED EXPERIENCE

As previously mentioned, wellbore restriction is our initial target problem. The problem is experienced during tripping operations and may escalate to failures if the wellbore is not properly cleaned. The causes of wellbore restriction failures can be grouped into three classes related to either equipment, wellbore or wellbore wall. Examples of failures within each of the three main classes are; Drill pipe twist off, Poor Hole Cleaning (cuttings, cavings) and Swelling Wellbore. Insufficient smoothness of the wellbore path can become evident in the form of pack-offs, took weight, high torque or high drag. Reoccurrence of such problems calls for reaming activity to hinder the restriction to escalate into stuck-pipe and lost circulation.

Determine the root cause of a failure

The objective is to determine the root cause starting out from three types of parameters: Direct observations – i.e. measurements, inferred parameters – i.e. values derived from observations, and interpreted events – i.e. particular concepts describing important states which require particular awareness or action. The parameters and causes are related in the ontology through intermediate concepts, such as intermediate causes or other states. Figure 6 illustrates the anomalous state of the wellbore and the formation. This state may return to normal by itself, and sometimes turn into a failure state as previously illustrated in Figure 4. In this paper we have specified root causes through the name of the failure. By specifying the subclasses of a failure as exemplified through Poor Hole Cleaning, the root cause is determined through pinpointing the failure to e.g. 'Cleaning Of Enlarged Hole' – the root cause is Hole Enlargement.

The task of the system is to determine which root causes or intermediate states are entailed or likely, given the parameters. Only some paths provide support for such a conclusion. In Figure 7 we have exemplified a case with the following reported observations (the observations are circled in red)

High Mud Flow Rate (here MFI Erosion)
Increasing Formation Exposure (here Increasing-I-Fm-Chem)
Pack Off
Took Weight
Low ROP
Narrow Event Distribution (along the axial length)
Increasing Drag
Low Wellbore Inclination

There is a path from all the observations either directly or indirectly to two different root causes; Enlarged Hole 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:

$$Path\ strength = \prod_{i=1}^{n} relation\ strength_i$$

where n is the number of serial relations. We observe that there are several explanatory paths from an observation to each target entity (the root cause entity).
The total explanation strength for each target entity is determined with the equation below.

$$Explanation\ strength = 1 - \prod_{i=1}^{m}(1 - path\ strength_i \times weight)$$

where m is the number of paths. The strength of a relation and which relation to apply between entities was decided by drilling experts, including relations like 'indicates' (with a strength of 0.4), 'leads to' (0.6) 'causes' (0.8). Calculated explanation strength will be a good indicator for identifying the possible root cause. In this example the explanation strength of Enlarged Hole was 0.088 while only 0.025 for Cuttings Accumulation.

Determine optimal repair activity through evaluation of outcome

A matching case can be used to inform the user about;

Time needed to clean (the most) similar wells
How was it done? Can it be performed alternatively?
Potential problems during 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 class A also is suitable for new cases of this class. We claim this is a fair assumption since 82 % of the cases in this class were similar enough to be selected. 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 again, repair methods 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 must be checked if it corresponds with recommended actions for the specific situation. After an incident has taken place, the user tries out a repair strategy. When 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 investigation and evaluation reports.

As it is now, we just recommend the Repair Activity applied in the best matching class. One could claim that Repair Activity in the selected case represents the accumulated experience in the field, However, the experience could be wrong, e.g. based on wrong interpretation of downhole behavior. If outcome-evaluation is not considered, the system will become static.

CONCLUSION

An on-line software tool has been successfully developed. It 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 outcome of repair. Experience embedded in a case is retrieved from data streams, and from documents, but also from the user and other experts during case generation and ontology building; during evaluation, etc. Cases representing complex domains like oil well drilling operations need to be related to a rich ontology since the case space is large. 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. We also claim that cases occurring in wellbores that exhibit escalating restrictions have built-in prediction capability. These wells are typically deep or long wells associated with long exposure time. Improvements are pending; new Indicators; new Events; higher quality of existing Events. All improvements will allow similar episodes to become more similar. They will open for formal and reliable prediction of root cause. Up to now, good engineering judgment dictates root cause. The correct root cause will improve quality of advises. Research is continuing on refining the system in response to industry feedback. We have exemplified the utilization of a CBR system directed towards reduction of downtime. It is at this stage merely a claimed reduction since the system has yet to be field-tested. When run in the field, the user will start testing recommendation 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. In fact, after the results reported here, Verdande Technology has developed and extensively tested a commercial and customer-targeted CBR system that utilizes many of the design principles of the reported system. That system has shown excellent accuracy and performance properties in real drilling settings (www.verdandetechnology.com).

REFERENCES

Aamodt, A. and Plaza, E. (1994) 'Case-based reasoning: Foundation issuers, methodological variations and system approaches', *Artificial Intelligence Communications*, Vol. 7, No 1, pp. 39-52.

Abdollahi, J., Carlsen, I.M., Randhol, P., Tenold, E., Haga, H.B. and Jakobsen, T. (2008) 'A Case-Based Approach to Understand the Complexity of Causal Connections Related to Well Integrity Problems', presented at *the 2008 IADC/SPE Drilling Conference*, Orlando, 4–6 March.

Brett, J., Ford, G.M.K. and Gahan, B.C. (1998) 'Successful Drilling Practices - An Experiment in Cooperation', *IADC/SPE Drilling Conference*, 3-6 March, Dallas.

Bhushan, V. and Hopkinson, S. C. (2002) 'A Novel Approach to Identify Reservoir Analogues', *European Petroleum Conference*, Aberdeen, 29-31 October.

Brown, L.P., Brown, L. and Hawkes, R.V. (2005) 'Rules of Thumb in Well Testing: What Works and Doesn't Work-and Why' *Journal of Canadian Petroleum Technology*, Vol. 44, No. 5.

Cheetham, W. and Watson, I. (2005) Fielded applications of case-based reasoning. *The Knowledge Engineering Review , Cambridge University Press*, Vol. 20, pp 321-323.

Datta, B.K., Ratnayake, C., Saasen, A. and Omland, T.H. (2005) 'Hole Cleaning and Pressure-Loss Prediction From a Bulk Transport Perspective', Paper SPE 96315 presented at *Offshore Europe*, 6-9 September, Aberdeen.

Gordon, H.J. (2006) 'Integrating Learning into Safety', *ASSE Professional Development Conference and Exposition*, Seattle, June 11 – 14.

Khajotia, B., Sormaz, D. and Nesic, D. (2007) 'Case-based Reasoning Model of CO2 Corrosion Based on Field Data', *Corrosion 2007, NACE International*, Nashville, March 11 – 15.

Kravis, S and Irrgang, R. (2005) 'A case bsed sy7stem for oil and gas well design with resk assessment', *Applied Intelligence*, Vol. 23, pp 39-53.

Obrst, L., Liu, H. and Wray, R. (2003) 'Ontologies for Corporate Web Applications' *AI Magazine,* Vol. 24 No. 3.

Mendes, J.R. P., Morooka, C. K. and Guilherme, I. R. (2003) ' Case-based reasoning in offshore well design' , *Journal of Petroleum Science and Engineering*, Vol. 40, pp 47– 60.

McCormack, G. (2010) 'An Industry upturn with a downside: Talent needs still loom large', *JPT*, May, 44 – 46.

Milter, J., Bergjord, O.G. Høyland, K. and Rugland, B. (2006) 'Use of Real-Time Data at the Statfjord Field Anno 2005', *Intelligent Energy Conference and Exhibition*, Amsterdam, 11-13 April.

Popa, A, et al. (2008) 'Case-based reasoning approach for well failure diagnostics and planning', SPE paper 114 229, presented at the *2008 SPE Western Regiounal and Pacific Section AAPG Joint Mtg*, Bakersfield, March 31 - April 2.

Staab, S. and Studer, R. (2009) 'Handbook on Ontologies', 2nd. ed. *Springer*, 811 pgs.

Valipour, S.S. and Skalle, P. (2009) 'Enhancing Decision Making in Critical Drilling Operations, SPE paper 12290, presented at *SPE Middle East Oil & Gas Show and Conference*, Bahrain, March 15–18.

Torsvoll, A. and Grotmol, Ø. (1999) 'Optimizing Contract Management and Cooperation Between Operator and Service Company', *Journal of Petroleum Technology*, Vol. 51, No. 2.

Valipour, S.S., Skalle, P. (2009) 'Enhancing Decision Making in Critical Drilling Operations, SPE paper 12290, presented at *SPE Middle East Oil & Gas Show and Conference*, Bahrain, March 15–18.

Valipour Shokouhi, S.S., Aamodt, A., Skalle, P. and Sørmo, F. (2009) 'Determining root causes of drilling problems by combining cases and general knowledge', Proceedings of the *8th International Conference on Case-Based Reasoning, ICCBR 2009*, Seattle, *Lecture Notes in Artificial Intelligence 5650, Springer Verlag, ISSN-0302-9743*, pp. 509-523.

Verdande Technology (2009), ' Harvesting knowledge to improve drilling performance in real time; A perspective on lowering NPT in difficult and critical wells'. White paper. (http://www.verdandetechnology.com/images/stories/verdande/publications/vt_whitepaper.pdf).

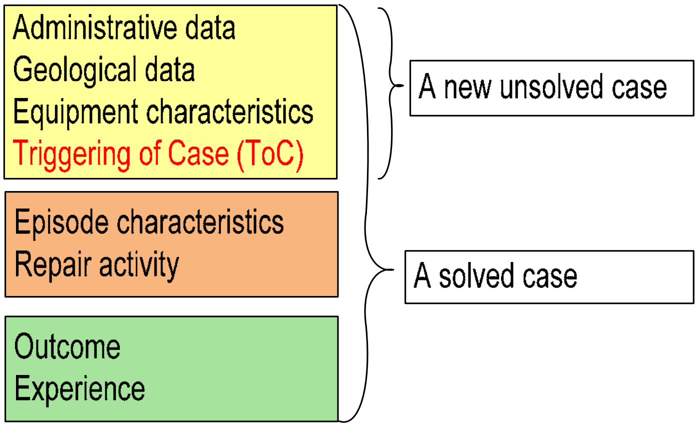
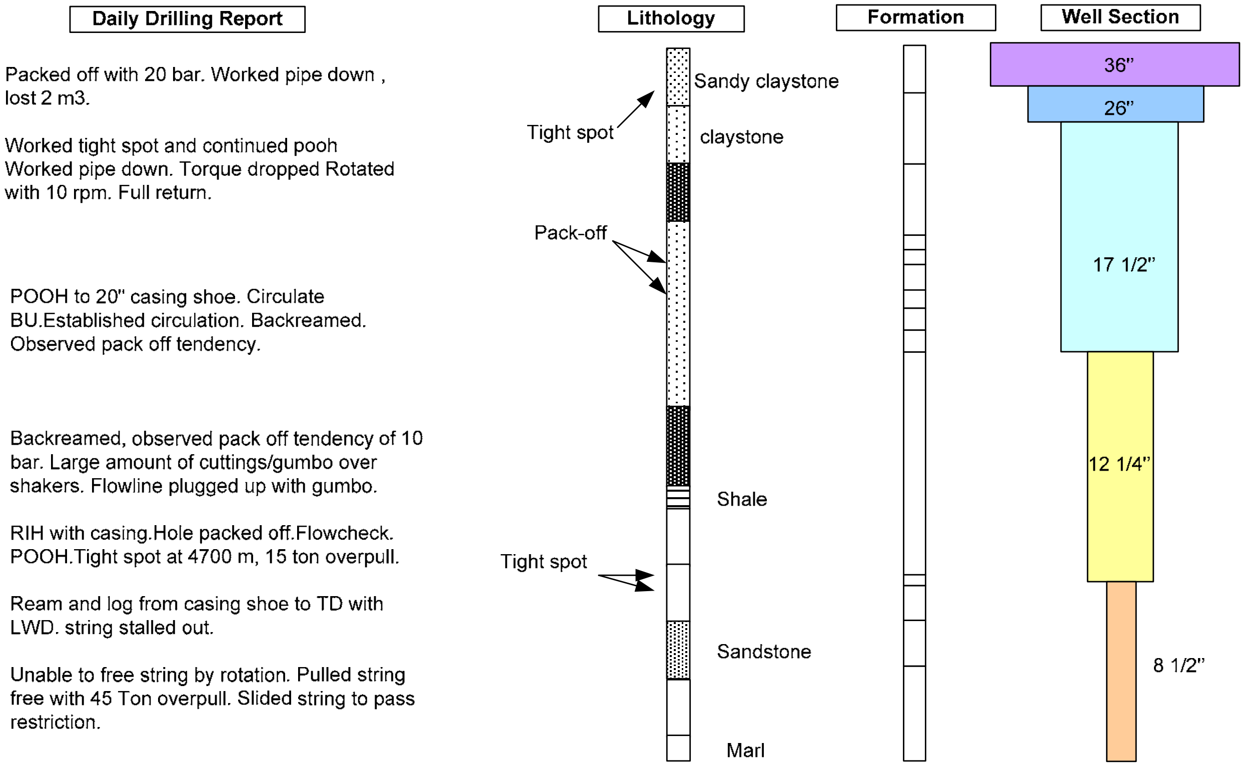


Fig 1. Selected format of case structure



Packed off with 20 bar. Worked pipe down , lost 2 m3.

Worked tight spot and continued pooh Worked pipe down. Torque dropped Rotated with 10 rpm. Full return.

POOH to 20" casing shoe. Circulate BU.Established circulation. Backreamed. Observed pack off tendency.

Backreamed, observed pack off tendency of 10 bar. Large amount of cuttings/gumbo over shakers. Flowline plugged up with gumbo.

RIH with casing.Hole packed off.Flowcheck. POOH.Tight spot at 4700 m, 15 ton overpull.

Ream and log from casing shoe to TD with LWD. string stalled out.

Unable to free string by rotation. Pulled string free with 45 Ton overpull. Slided string to pass restriction.

Fig 2. Evaluation and initiation of a case building process, here on basis of Daily Drilling Report.

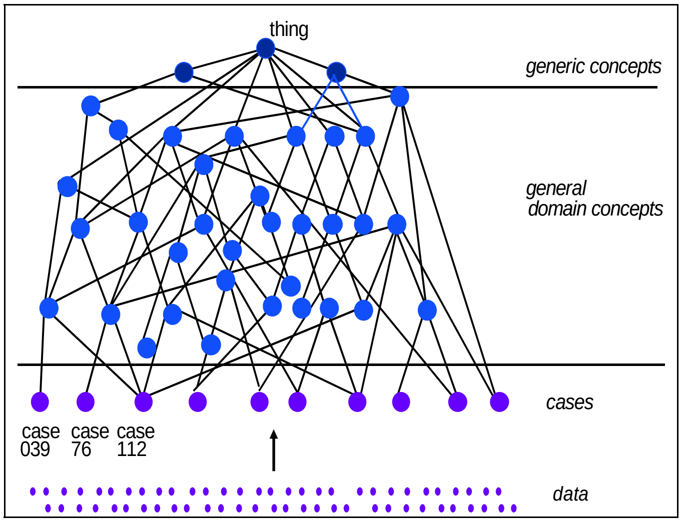


Figure 3. Example of Ontology. It consists of general knowledge in the upper levels and of specific knowledge in the lower levels. Most specific knowledge are stored in cases as defined by the process data.

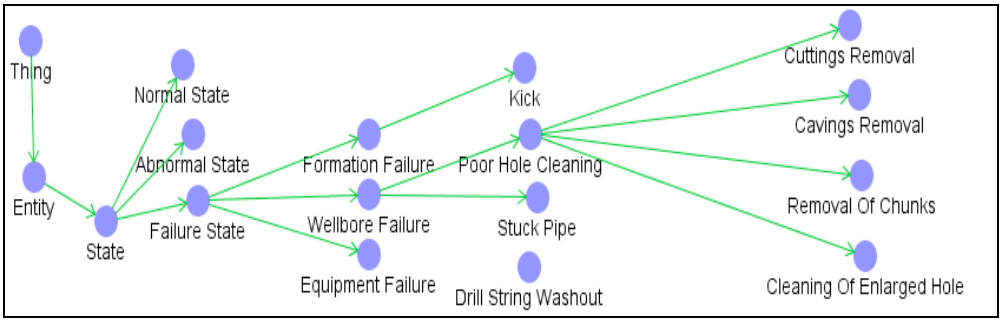


Figure 4. Failure State and its sub classes are indicated by an arrow. Symptoms activated during an episode are point to a specific Failure Subclass.

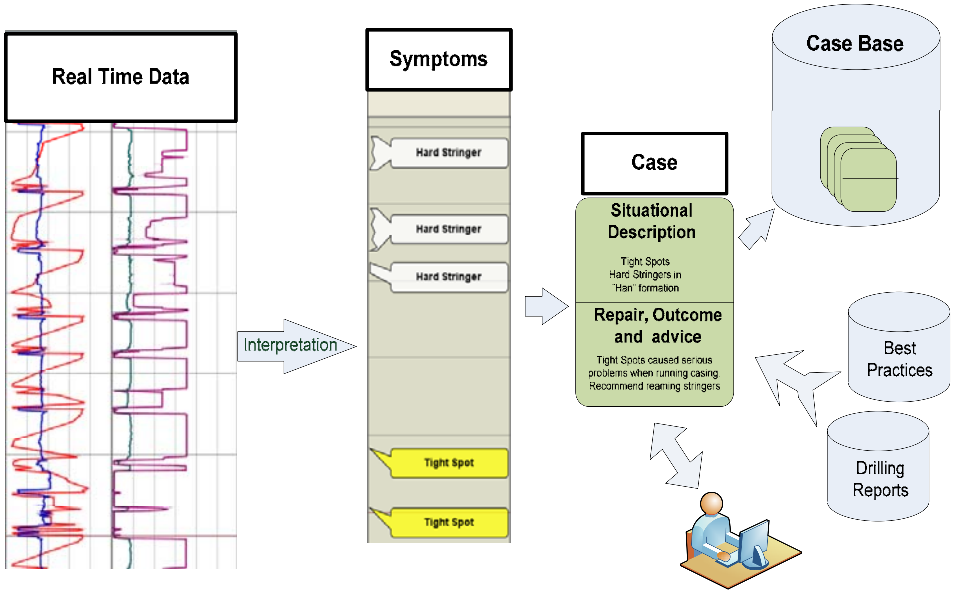


Fig 5. Sources and transfer of experience during case building: Real-time data (left) and Documents (to the right). An expert is needed in the process of creating cases, either they are created from historical logs/reports or from real time data.

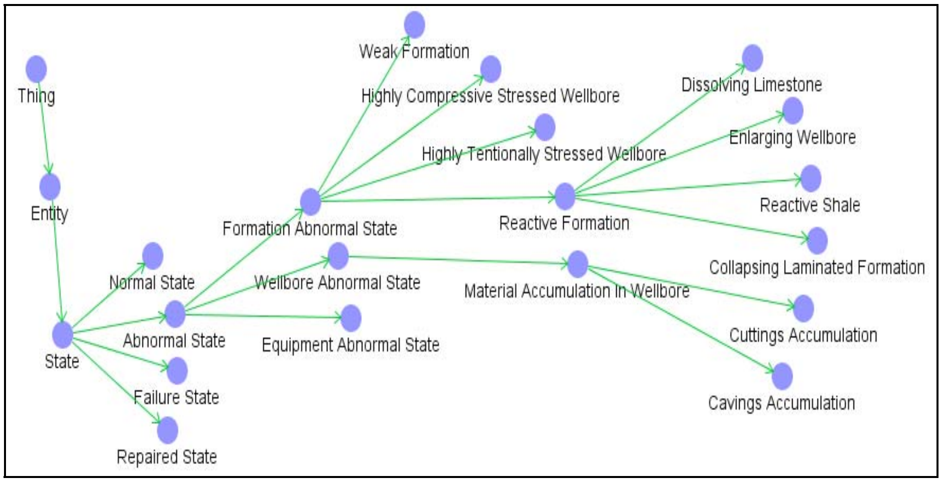


Fig 6. Abnormal State. Its sub classes are indicated by arrows.

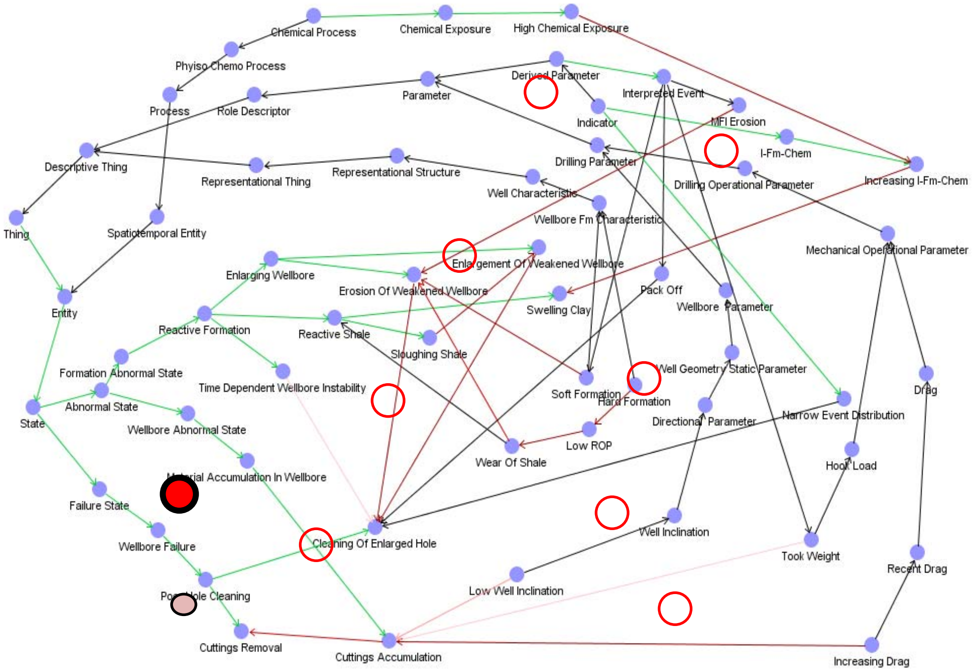


Fig 7. Failure State. Symptoms activated during the episode, pointing to a specific Failure.