KNOWLEDGE-BASED DECISION SUPPORT IN OIL WELL DRILLING

Combining general and case-specific knowledge for problem solving

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Abstract: Oil well drilling is a complex process which frequently is leading to operational problems. The process generates huge amounts of data. In order to deal with the complexity of the problems addressed, and the large number of parameters involved, our approach extends a pure case-based reasoning method with reasoning within a model of general domain knowledge. The general knowledge makes the system less vulnerable for syntactical variations that do not reflect semantically differences, by serving as explanatory supportfor case retrieval and reuse. A tool, called TrollCreek, has been developed. It is shown how the combined reasoning method enables focused decision support for fault diagnosis and prediction of potential unwanted events in this domain.

Key words: Ontologies, Case-Based Reasoning, Model-Based Reasoning, Knowledge Engineering, Prediction, Petroleum Engineering,.

1. INTRODUCTION

This paper presents a new level of active computerized support for information handling, decision-making, and on-the-job learning for drilling personnel in their daily working situations. We focus on the capturing of useful experiences related to particular job tasks and situations, and on their reuse within future similar contexts. Recent innovations from the areas of data analysis, knowledge modeling and casebased reasoning has been combined and extended. The need for such a method was driven by the fact that current state-of-the-art technology for intelligent experience reuse has not been able to address the complexity of highly data-rich and information-intensive operational environments. An operational environment, in the context of this research, refers to a job setting where people's decisions quickly lead to some operational action, which in turn produce results that trigger decisions about new actions, and so on. The overall objective of this work has been to increase the efficiency and safety of the drilling process. Efficiency is reduced due to unproductive downtime. Most problems (leading to downtime) need to be solved fast. Since most practical problems have occurred before, the solution to a problem is often hidden in past experience, experience which either is identical or just similar to the new problem. The paper first gives an overview of our combined case-based and model-based reasoning method. This is followed, in section 3, by an oil well drilling scenario and an example from a problem solving session. This is followed by a summary of related research (section 4), and a discussion with future works in the final section.

2. KNOWLEDGE-INTENSIVE CASE-BASED REASONING

Based on earlier results within our own group[1-4], as well as other related activities, the method of case-based reasoning (CBR) has proven feasible for capturing and reusing experience and best practice in industrial operations[5-7]. CBR as a technology has now reached a certain degree of maturity, but the current dominating methods are heavily syntax-based, i.e. they rely on identical term matching. To extend the scope of case matching, and make it more sensitive to the meaning of the terms described in the cases - including their contextual interpretation - we suggest a method in which general domain knowledge is used to support and strengthen the case-based reasoning steps. The general domain knowledge serves as explanatory support for the case retrieval and reuse processes, through a model-based reasoning (MBR) method. That is, the general domain knowledge extends the scope of each case in the case base by allowing a case to match a broader range of new problem descriptions (queries) than what is possible under a purely syntactic matching scheme. Integration of CBR and MBR is referred to as "knowledge intensive case-based reasoning" (Ki-CBR). Ki-CBR allows for the construction of explanations to justify the possible matching of syntactically dissimilar – but semantically/pragmatically similar – case features, as well as the contextual (local) relevance of similar features. Earlier research reported from our group has also addressed this issue. However, the resulting architectures and implemented systems were basically CBR systems with a minor model-based addition, and tailored to specific problems. This has been taken further into a novel and flexible system architecture and tool – called TrollCreek - in which the model-based and case-based components may be combined in different ways.

2.1 The Model-Based Component

Methods for development of knowledge models for particular domains (e.g.drilling engineering) have over the last years improved due to contributions both from the knowledge-based systems field of artificial intelligence, and the knowledge management field of information systems. The knowledge models are often expressed in a standard language (XML-based). This facilitate that knowledge structures can end up in shared libraries, to become available for others. During the development of a knowledge modelling methodology for the petroleum technology domain, existing, more general, frameworks and methodologies, in particular CommonKADS, Components of Expertise, and CBR-related methodologies[8-10] were adapted.

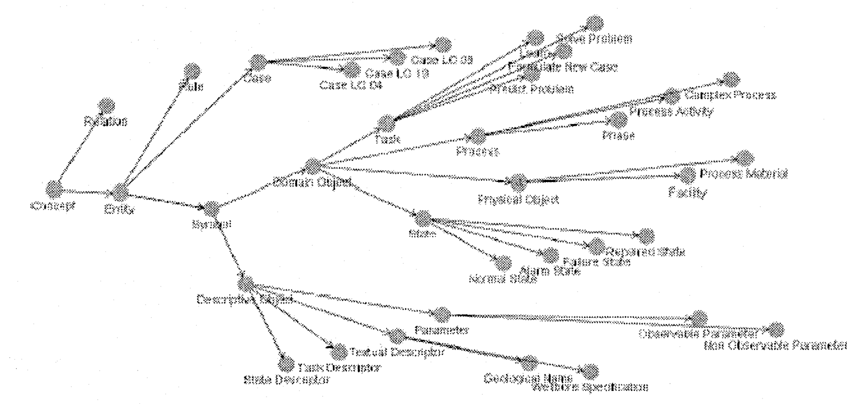

Figure 1. A part of the top-level ontology, showing concepts linked together with structural relations of type "has subclass". Each relation has its inverse (here "subclass-of", not shown).

At the simplest level, the TrollCreek general domain model can be seen as a labeled, bi-directional graph. It consists of nodes, representing concepts, connected by links, representing relations. Relation types also have their semantic definition, i.e. they are concepts. The uppermost ontology of the TrollCreek model is illustrated in Figure 1. Different relations have different numerical strength, i.e. a value in the range 0-1, corresponding to a relation's default "explanatory power". For example, a "causes" relation has default strength 0.90, a "leads to" relation 0.80, and an "indicates" relation 0.50. All parameter values that the system reasons with are qualitative, and need to be transformed from quantitative values into qualitative concepts, as exemplified in Table 1. The entity "Weight On Bit" (WOB) is taken as an example. WOB is a subclass of Operational Parameter which is subclass of Observable Parameter in our ontology model. Currently, the oil drilling domain model contains about 1300 concepts related through 30 different relation types.

Table 1. Qualitative values and their definitions

Qualitative value	Quantitative value	Quantitative definition
Normal wob	wob-30	average value over last 30 m of drilling
High wob	wob-1 / wob-30 > 1.2	wob-1 = average value over last 1 m of drilling
Low wob	wob-1 / wob-30 < 0.8	

In Table 2 some relations between entities (other than subclass) are presented.

Table 2. Relations between some concepts.

Node 1	Relation	Target node
Background gas from shale	implies	Increasing pore pressure
Back reaming	leads to	Negative ecd
Balled bit	occurs in	Wbm
Blowout	enabled by	Kick
Bo through bop/annulus	caused by	Failed to close bop

2.2 The Case-Based Component

Cases are descriptions of specific situations that have occurred, indexed by their relevant features. Cases may be structured into subcases at several levels. They are indexed by direct, non-hierarchical indices, leaving indirect indexing mechanisms to be taken care of by the embedding of the indices within the general domain model. Initial case matching uses a standard weighted feature similarity measure. This is followed by a second step in which the initially matched set of cases are extended or reduced, based on explanations generated within the general domain model. Cases from the oil drilling domain have been structured in a manner which makes them suitable for finding the solution of a problem and/or search for missing knowledge. All cases therefore contain the following knowledge:

• characteristics that give the case a necessary, initial "fingerprint", like owner of problem (operator); Place/date; Formation/geology; installation/well section; depth/mud type

• definition of the searched data / recorded parameter values / specific errors or failures

• necessary procedures to solve the problem, normative cases, best practice, repair path consists normally of a row of events. An initial repair path is always tried out by the drilling engineer and usually he succeeds. If his initial attempts fail, then the situation turns into a new case, or a new problem.

• the final path, success ratio of solved case, lessons learned, frequently applied links From a case, pointers or links may go to corporate databases of different formats. Typical examples are logging and measurement databases, and textual "lessons learned" documents or formal drilling reports.

3. OIL WELL DRILLING SCENARIO

During oil well drilling the geological object may be as far as 10 km away from

the drilling rig, and must be reached through selecting proper equipment, material

and processes. Our work is addressing all phases of the drilling process; planning

(for planning purposes the TrollCreek tool is addressing the drilling engineer), plan

implementation (addressing the driller and the platform superintendent) and post

analyses (addressing the drilling engineer and management). Of all possible

problems during oil well drilling we have in this scenario selected one specific

failure mode; Gradual or sudden loss of drilling fluid into cracks in the underground.

This failure is referred to as Lost Circulation. Lost circulation (LC) occurs when the

geological formation has weaknesses like geological faults, cavernous formations or

weak layers. The risk of losses increases when the downhole drilling fluid pressure
becomes high, caused by i.e. restrictions in the flow path or by the drilling fluid
becoming more viscous.

3.1 An Example

Assume that we are in a situation where drilling fluid losses are observed, and the situation turns into a problem (Lost Circulation). See the case description to the left in Figure 2. TrollCreek produces first of all a list of similar cases for review of the user, see Figure 3, bottom row. Testing of Case LC 22 suggests that Case LC 40 is the best match, with case 25 as the second best. Inspecting case 25 shows a matching degree of 45%, and a display of directly matched, indirectly (partly) matched, and non-matched features. Examination of the best-matched cases reveals that Case LC 40 and 25 are both of the failure type Natural Fracture (an uncommon failure in our case base). By studying Case LC 40 and 25 the optimal treatment of the new problem is devised (the "has-solution" slot, see right part of figure 2), and the new case is stored in the case base. The user can choose to accept the delivered results, or construct a solution by combining several matched cases. The user may also trigger a new matching process, after having added (or deleted) information in the problem case. The user can also browse the case base, for example by asking for cases containing one specific or a combination of attributes.

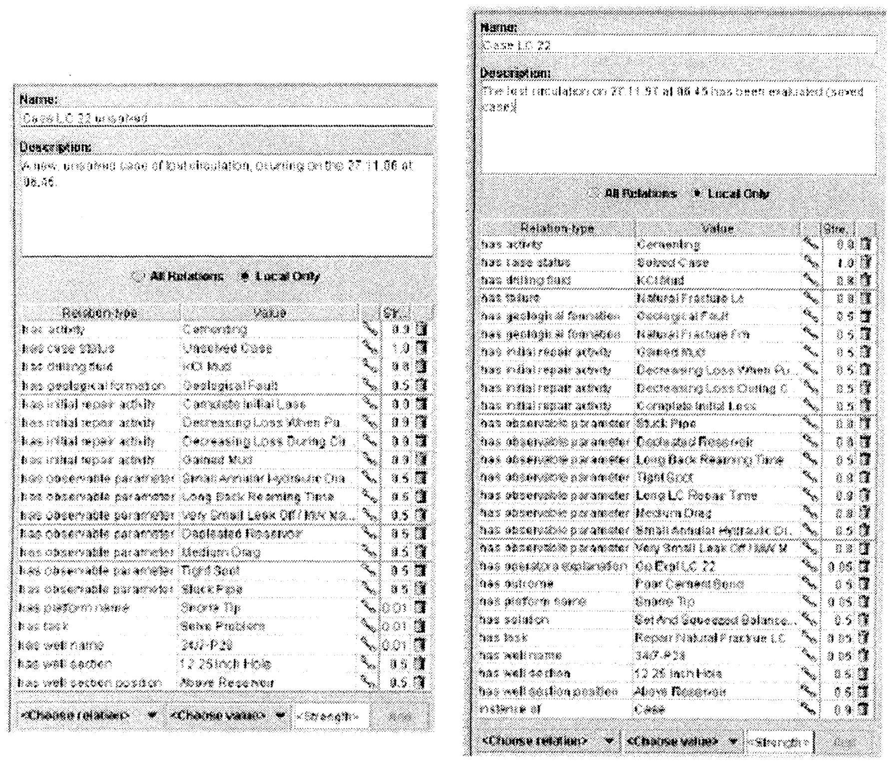

Figure 2. Unsolved case (left) and the corresponding solved case (right) of Case LC 22.

3.2 The role of general domain knowledge

A model of causal and other dependency relations between parameter states, linked within a set of taxonomical, part-subpart, and other structural relations, constitutes the core of the general domain model. This enables the system to provide a partial explanation for the reason of a failure. Figure 4 shows parts of the explanation structure explaining why Case LC 22 is a problem of the type Natural Fracture. An important notion in identifying a failure mode is the notion of a non-observable parameter, i.e. a parameter which is not directly measurable or observable, usually related to conditions down in the well. In Figure 4, examples of such parameters are Annular Flow Restrictions, Increasing Annular Pressure,Decreasing Fracture Pressure, Leaking Fm, Large LCD, Pressure Surge, High Annular Pressure. An important reasoning task is to relate failures to possible non-observable parameters, using the knowledge model, then relate these to other measured parameters until a set of possible failure modes are suggested.

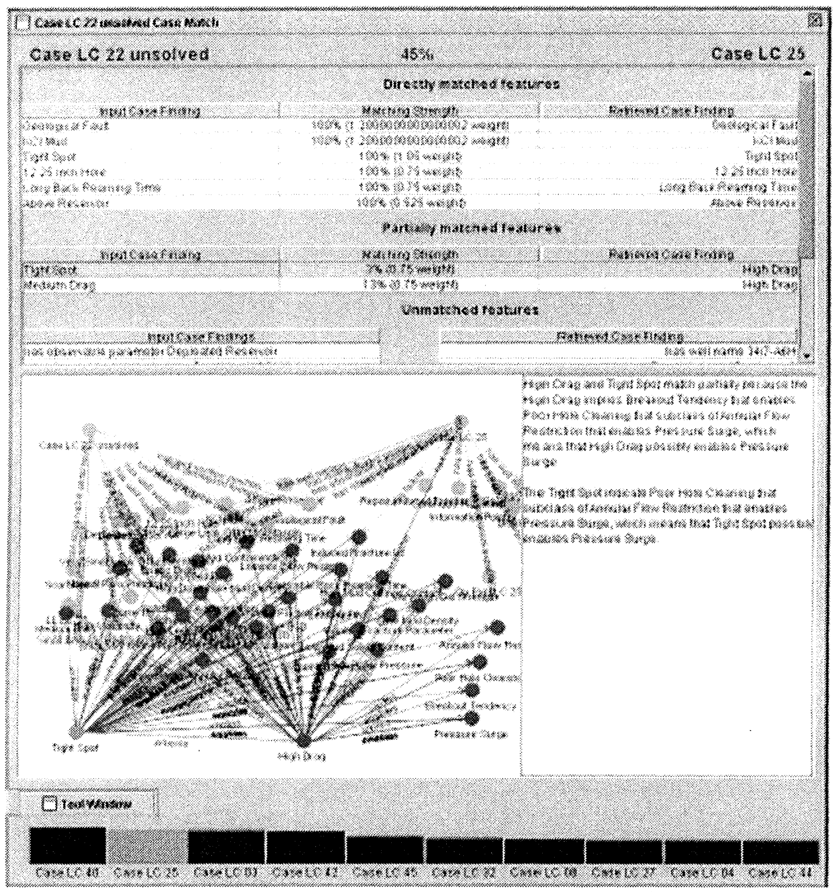

Figure 3. Results of matching a new case (Case LC 22 unsolved) with the case base

Indirect (partial) matching of case features is exemplified in Figure 3. The lower half of the display (hiding all but one of the unmatched features), shows a graphical display of concepts involved in the matching, and a textual description explaining the match. Identifying a failure and a repair for the failure are two types of tasks that the system can reason about. An explicit task-subtask structure is a submodel within the domain model, which is used in controlling the reasoning process. This is exemplified in Figure 5, which also shows (upper right) tasks linked to failure states. States are also interlinked within a state structure (not shown). By combining task and state models, with causal reasoning as illustrated in Figure 4, a solution may be found by model-based reasoning within the general domain model, even if a matching case is not found. If so, the system will – as shown before - store the problem solving session as a new case, hence transforming general domain knowledge, combined with case-specific data, into case-specific knowledge.

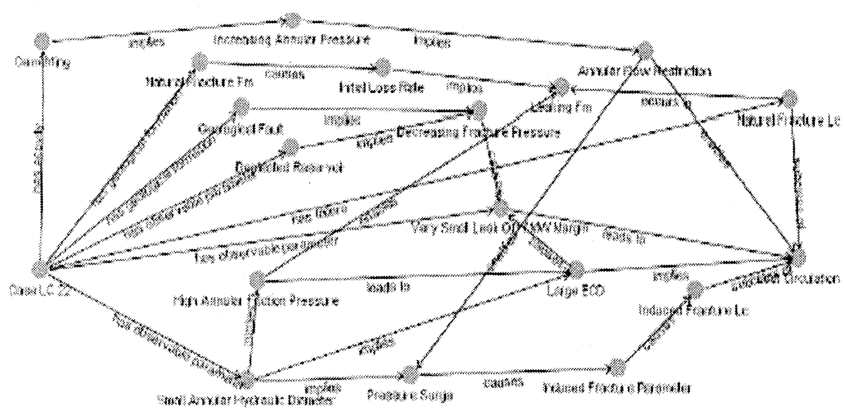

Figure 4. Some of the explanation paths behind the failure in Case LC 22

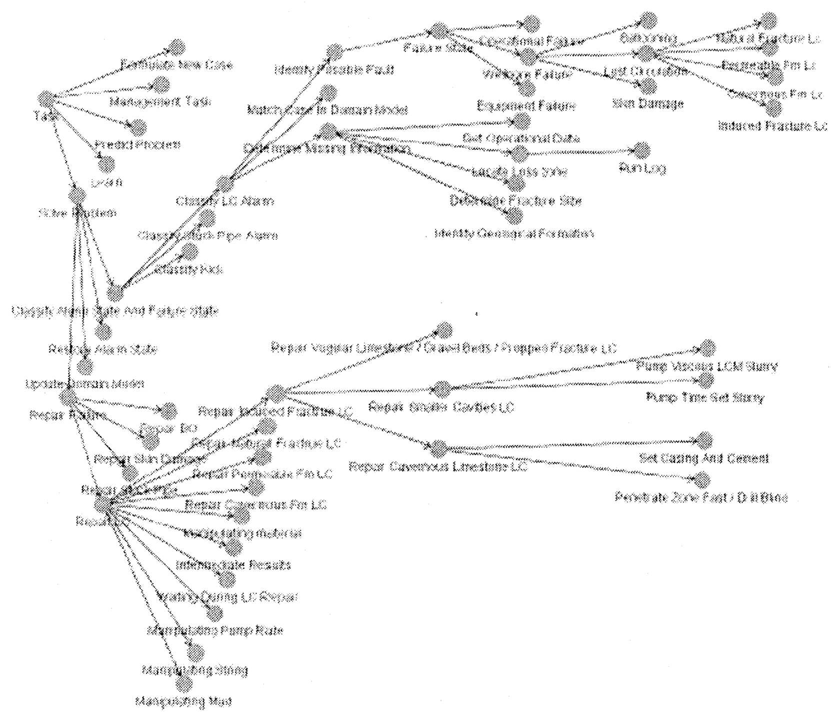

Figure 5. Partial task hierarchy, linked with parts of a failure hierarchy

4. RELATED WORK

Several oil companies recognize the need to retain and centralize the knowledge and experience of the organization, among other reasons due to outsourcing and spreading of knowledge. Generally, diagnostic tools represent the largest area of application for AI systems[11]. Amoco/Phillips and Shell serve as examples of oil companies that have reached far with respect to implementation of experience transfer tools. Amoco/Phillips[12] presents a heuristic (experience based) simulation approach to the Oil Well Drilling domain, based on data sets of 22 actual wells. The accumulated data are treated statistically and fitted to a model based on combining human thought, artificial intelligence and heuristic problem solving. The model will adapt to a specific geological area, and capture experience, reuse it and gradually improve and learn. They encompass and model the complete drilling process, rather than specific subproblems. Their approach is therefore less focused than our approach. Parallel to this activity CIRIO[13] is leading a "Drilling club" in which all members contribute with well data from around the world. By means of a CBR technique, previous, analogous wells or aspects of well are selected through similarity matching, and adapted to new wells. Shell[14] has taken a similar approach as above, as they have selected the reservoir as a case entity. A common reservoir knowledge base, containing relevant reservoir information like reservoir description, development plans, production reports, etc., can be shared by any Shell staff around the world. The individual user may retrieve the best matching reservoir through similarity matching (reservoir analogues). The Shell approach represents, on the one hand, a more ambitious approach than ours, but on the other a less focused one. CBR are known to be well suited for maintenance of other complex processes, related to our domain. Mount and Liao[11] describe a research and learning prototype which helps find the answers and explanations of fatigue-cracking failures in a power generation process. The prototype covers both support in failure investigation and suggests the primary cause of a failure in a priory list, leaving the ultimate decision to the user. Netten[15] points out that CBR provides significant advantages over other techniques for developing and maintaining diagnosis systems, while accuracy and coverage may be low. By comparing with surveillance of the process this is certainly true. Surveillance can be performed at high accuracy but to a limited amounts of selected parameters. Monitoring of torque and drag[16] is promising for predicting wellbore cleaning / stuck pipe situations. High accuracy and coverage of CBR systems can be improved but comes at a high price. A large case library and complex ontology must be developed. Our approach differs from the above in the combination of case-specific and general domain knowledge. Further, the model-based reasoning module in TrollCreek assumes open and weak theory domains, i.e. domain domains characterized by uncertainty, incompletes, and change. Hence, our inference methods are abductive, rather than deductive, forming the basis for plausible reasoning by relational chaining[17].

5. CONCLUSION AND FUTURE WORK

As has been described, a new tool for handling knowledge-intensive case-based reasoning has been developed, and is now being tested. New cases are matching similar past cases with a high degree of user credibility, due to the ability of the system to justify its suggestions by explanations. Work related to failure diagnosis and repair is presented in this paper. Ongoing, parallel work includes prediction of unwanted events before they occur – also in the oil drilling domain, incorporating time-dependent cases and temporal reasoning[15]. Another challenge is how to automatically update the general domain model based on data, where we study probabilistic networks as a data mining method[2,18]. Additionally, work has been started to improve the knowledge acquisition and modeling methodology for both general and case-specific knowledge[10], automatically generate past case descriptions from text reports, and to facilitate this type of decision support in a mobile-computing environment. On the agenda for future research is extending the representational capacity of the system, e.g. to handle flexible forms of decision rules and conditionals on relationships. In the drilling industry the engineers tend to group problem related knowledge into decision trees. Decision trees are inherently instable, and alternative trees may produce different results[19]. A combination of the two may work well, our cases being the exceptions of the more rule based tree. Some frequently reoccurring problems may gradually (depending on failure rate) turn into a decision rule. Such problems will then enter the default best practice of the oil company. Best practice, or lessons learned, are notions of large interest in the oil drilling industry. Others have also investigated usefulness of case-based support tools for capturing lessons learned[20]. The approach presented in this paper is a contribution to a total strategy of retaining and putting useful knowledge and information to use when needed. We are currently discussing this issue, on a broader scale, with some oil companies. The challenges here are essentially twofold: One is to integrate a knowledge-based decision support tool smoothly into the other computer-based systems in an operational environment. The other, and not less challenging, is to integrate computerized decision support into the daily organizational and human communication structure on-board a platform or on shore.

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