Artif Intell Rev
DOI 10.1007/s10462-011-9310-2

An overview of case-based reasoning applications in drilling engineering

Samad Valipour Shokouhi · Pål Skalle · Agnar Aamodt

Abstract Application-oriented research in the area of case-based reasoning has moved mature research results into practical applications. This paper presents an overview of different applications of case-based reasoning (CBR) in petroleum engineering, with focus on the drilling process, based on a survey and comparative evaluation of different applications. The numbers of papers, research groups, and experimental systems are indicative of the importance, need, and growth of CBR in different industries. A clear growing trend has been seen in the oil and gas industry over the last 5–10 years. In this paper we present the evolving story of CBR applied to problems in drilling engineering. We show that drilling engineering is an application domain in which the systematic storage and situation-triggered reuse of past concrete experiences provide significant support to drilling personnel at various levels. Some CBR systems have been successfully deployed in operational settings. With increased understanding of the complexity of drilling operations and continuous development of CBR and combined methods, the future potential is significantly higher.

Keywords Case-based reasoning · Decision support · Petroleum engineering · Oil well drilling

S. V. Shokouhi (✉) · P. Skalle
Department of Petroleum Technology (IPT), Norwegian University of Science and Technology (NTNU), Trondheim, Norway
e-mail: valipour@ntnu.no

P. Skalle
e-mail: pal.skalle@ntnu.no

A. Aamodt
Department of Computer and Information Science (IDI), Norwegian University of Science and Technology (NTNU), Trondheim, Norway
e-mail: agnar.aamodt@idi.ntnu.no

Published online: 03 January 2012

1 Introduction

Case-based reasoning (CBR) is defined as the branch of artificial intelligence (AI) concerned with solving problems by reuse of past experiences. Case-based reasoning is an approach to problem solving and decision making where new problems are solved by finding one or more similar previously solved problems, called cases, and re-using them in new problem situations (Aamodt and Plaza 1994; Kolodner 1992). CBR may be used on its own, or integrated with other reasoning modalities to provide more accurate results by compensating the shortcomings of one approach through use of the strengths of another (Marling et al. 2005).

The aim of the study reported here is to show what possible benefits CBR can provide to the oil and gas drilling industry. The number of publications on the application of CBR in drilling operations indicates that this is a feasible method to reduce the cost and increase the safety of drilling operations, by explicitly capturing and reusing previous experiences, hidden in reports and/or known by experts.

Oil and gas are the main energy sources in many countries. To supply world oil consumption, new wells are continuously demanded. Such needs have motivated and inspired people around the world to apply dedicated artificial intelligence methods, including case-based reasoning, in drilling operations. Oil well drilling is a complex operation. Problems frequently occur when drilling several kilometers through different geological formations. Each well may experience both similar and new problems during the drilling operation. Offshore drilling of an oil well is also an expensive operation, costing typically 250,000 US$ per day per rig. Access to experts for the purpose of solving swiftly problem and knowledge acquisition is limited.

In a previous conference paper (Shokouhi et al. 2010a) we presented a shorter and less elaborated overview, with a focus on work from our own group. This paper has been substantially extended to cover for other influential work as well, to the degree their documentation has been available. This paper further contains a more thorough treatment of the drilling domain as an application area for CBR.

The following section presents some milestones on the CBR road from academic studies to a mature industrial tool. In Sect. 3 we review applications of CBR in drilling operations. Section 4 explains the applications of CBR in other sub-domains of petroleum engineering. The last section summarizes and concludes on the CBR's state of the art in petroleum engineering.

2 History of CBR from academia to industry

CBR enables utilization of specific knowledge of previously experienced, concrete problem situations. A CBR system requires a good supply of cases in its case database. The retrieval task starts with a problem description, and ends when a best matching previous case has been found. A new problem is solved by finding a similar past case, and reusing it in the new problem situation. Sometimes a modification of the solution is done to adapt the previous solution to the unsolved case. It is important to emphasize that CBR also is an approach to incremental and sustained learning; learning is the last step in a CBR cycle (Aamodt and Plaza 1994; Kolodner 1993), as described in chapter 3. A CBR system can also enhance its reasoning power through the explicit representation and use of generalized knowledge about a specific domain. A classical example is the CASEY system, a medical application to diagnose heart failures (Koton 1988). Later, other frameworks for building knowledge-based systems that integrate CBR with rule-based reasoning (RBR) and model-based reasoning (MBR) were introduced by other groups (e.g., Abel et al. 1996 and Aamodt 2004).

The CBR approach was initiated roughly 35 years ago, assuming the work of Schank and Abelson (1977) to be considered the underlying early origins of CBR. Several academic studies were triggered that brought the idea further, especially continued work on the role of memories in learning and problem solving (Schank 1982). This boosted further research in the early 80s, particular in the US on different CBR approaches, underlying theories, and experimental systems (Kolodner 1993).

One of the earliest successful and influential applications was developed at Lockheed, a US aerospace company (Mark 1989). Modern aircrafts contain parts made of composite materials which must be cured in large industrial autoclaves. These parts have different characteristics requiring different autoclave heating and cooling profiles. This is complicated by the fact that many parts need to, for reasons of sufficient throughput, be placed together in a single large autoclave, and the fact that the parts interact to alter the heating and cooling characteristics of the autoclave. Operators of Lockheed's autoclaves relied on previous successful layouts to decide how to lay out parts in the autoclave. They were inspired to develop CLAVIER, the system to assist autoclave operators to reuse previously successful loadings. New successful layouts provided by operators were added to a library to improve the performance of CLAVIER. The system retrieved or adapted successful layouts 90% of the time. The results showed that the developed system had capability to help solve problems quicker and more optimal than without the system. CLAVIER's success also triggered successful utilization of the approach by other companies (Mark 1989; Watson and Marir 1994).

Different types of applications addressed by CBR in the oil and gas industry are shown on the right side of Fig. 1. The left part of the figure shows the evolutionary path of the projects that we have studied, which may vary from initial methodologies to field evaluated systems. The last phase, field evaluated, captures represent systems that have been commercially deployed, such as CLAVIER.

3 Case-based reasoning (CBR)

Case based reasoning is an approach to solving problems, reusing experiences from concrete problems solved in the past and gaining lessons learned for future use. The CBR approach is particularly suitable in domains for which concrete human experiences play a significant role in human problem solving. CBR works on the basic principle that similar problems often have similar solutions (Aamodt and Plaza 1994; Marling et al. 2005).

Basically, every CBR system follows a cyclic process of four main steps; Retrieve, reuse, revise, and retain (shown in Fig. 2). The similarity measure computes the similarity between a new case and previous cases restored in the case base. Depending on the application domain and features used for describing cases, a simple or more complex measure can be applied (Cunningham 2008; Finnie and Sun 2002). Solutions from past cases may not directly be reusable, in which situations they should be adapted to better fit the new problem. The suggested case solution is evaluated and revised if needed. Finally, the revised case is retained to provide sustained learning.

When it comes to application-oriented schemes, most of the presented systems follow the four main steps of the CBR cycle. This indicates that CBR is a well-established approach that facilitates implementation of the methodology in petroleum engineering as well as other domains.

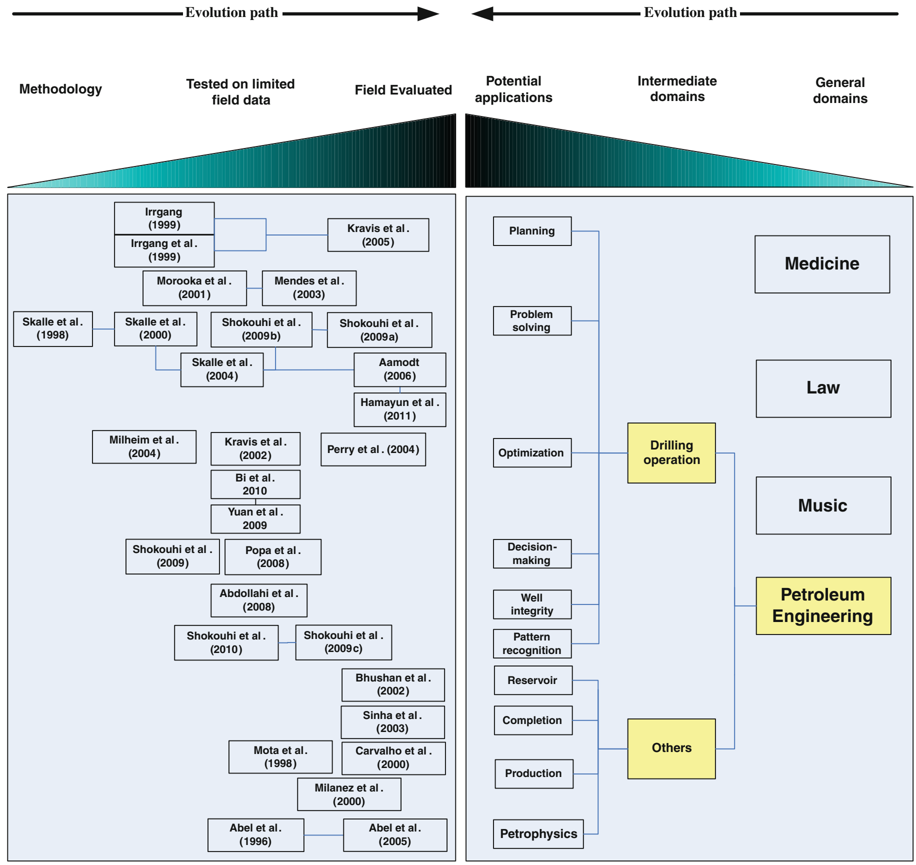
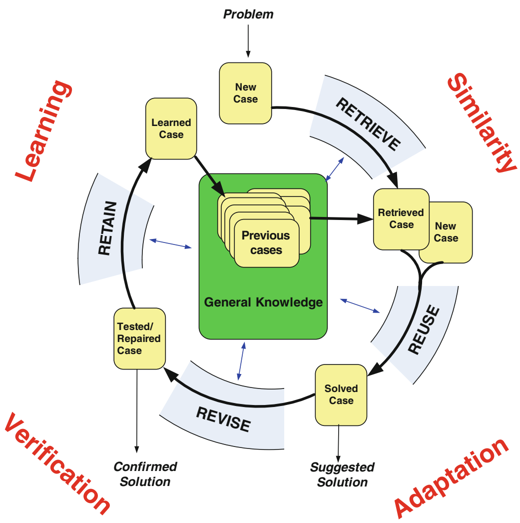


Fig. 1 Applications of the CBR implemented in the petroleum engineering domain

Fig. 2 The CBR cycle modified from Aamodt and Plaza (1994)



4 Applications in drilling

Advanced technologies and equipments are invented and employed in the drilling industry to reduce cost and increase productivity and safety of drilling operations. Drilling an offshore well, for example, may typically take 1 month involving high investments and high daily costs. Generally speaking, the drilling industry is a highly technology-dependent industry. Therefore, any sorts of tool or equipment that can improve the drilling operation are essential and are demanded during planning and during operation. Case-based reasoning has shown to provide effective support for several tasks related to drilling. Optimization of drilling plans, which are highly repetitive, can be achieved through CBR. The CBR method is also used for solving operational problems. Information gathered via the problem analysis process may be used in order to make decisions on how to proceed further. Cases in a CBR system can be kept to predict upcoming situation through evolving anomalous sequences of measurement data.

The applications of CBR in drilling operations have been demonstrated by different groups around the world and are presented in more detail in the following sections, each section describing a particular application focus.

4.1 Planning

Planning a well in an optimal manner is a complex task and highly experienced engineers are needed. As well as using all the information from other disciplines, such as seismic and geology, the experience and analysis of neighboring wells is essential for a good well plan.

CBR has been tried in the planning phase of oil well drilling by different groups around the world. One of the first applications of CBR in this area was documented by the Australian research organization CSIRO (Irrgang et al. 1999a,b), and later refined (Kravis and Irrgang 2005). The technique was applied to derive alternate drilling plans based on previously drilled wells. Each well was represented as one case. A case structure has three levels. The three levels are: groups of cases, groups of attributes and groups of defined drilling phases and operations. The proposed system, Genesis, can use multiple cases at varying levels of generalization. Moreover, it uses automated tools to extract knowledge and indexes for the case base from text data.

Mendes et al. (2001) presented an application of CBR in offshore well design. The result of that work was a formalization of the methodology for planning of an oil well in a case-based reasoning context. They used fuzzy set theory (Zadeh 1965) for the indexing and matching of index features.

Mendes and his colleagues implemented a genetic algorithm (GA) to determine the proper trajectory and other pertinent information for drilling. The evolution in a genetic algorithm usually starts from a set of solutions called an initial population (Whitley 1994). The initial population in that system is the cases retrieved via CBR. The proposed well trajectories have to be optimized by other well-known simulators starting from the well created by the genetic algorithm (Mendes et al. 2003). The most recent system is a continuation of past work (Morooka et al. 2001), which was moved from research into a real world experimental setting.

4.2 Operational problem solving

When drilling several kilometers through different geological formations problems frequently occur. The sensors installed at the surface as well as downhole in the drill string and bottom-hole assembly help to run the drilling process smoothly. Data via sensors are transmitted and translated to a suitable format in order to be interpreted by the drilling crew. In addition to real-time data, documents such as daily drilling reports and end of well reports are produced for every single well, and modern tools are becoming very helpful for these documentation tasks. The reports are valuable resources in which solutions for most of the past problems are expressed. Descriptions of situations in these reports contain the occurring problems and their proposed solutions. There will typically also be links to real-time data of relevance to what is being written down. In spite of these modern and valuable remedies, problems occur and repeat themselves, creating a demand for more advanced decision support methods such as CBR.

In most CBR approaches, an abnormal situation triggers the capturing of a case. This means that whenever a new interesting problem occurs, a case is built and stored in the case database. In addition, some non-problem cases are often also stored. In particular, it is used to store "good" cases that are somewhat similar to "bad" cases, in order to better discriminate between problems and non-problems. In brief, real episodes, in terms of previously solved situations, are the core of the reasoning process in which new problematic situations are resolved and explained.

Skalle et al. (1998) pioneered the employment of the CBR method for operational problems in the drilling industry. Their initial work was at the conceptual and design levels. *Stuck pipe* incidents from an operator over a 6 years period were statistically analyzed. The results led them to select characteristic parameters for cases and build a knowledge model. Their early paper basically presented a statistical analysis with a focus on development of the relevant domain knowledge model and case structure. Two years later, they implemented a system for prevention of unwanted events in the domain of offshore oil well drilling (Skalle et al. 2000). They introduced how to build a case in oil well drilling, mostly based on relative static parameters; relative to the normal or expected parameters' values. Static parameters do not change much between measurements. Their focus was on lost circulation, which means that some of the drilling fluid that always fills the gap between the drill string and the well wall gets lost into fractures in the geological formation. They built fifty cases on the basis of information from one North Sea operator. A general domain model was used to allow also for matching of non-identical features that were related in the model. This type of integrated reasoning, CBR and knowledge model, is referred to as knowledge-intensive CBR (KiCBR) (Aamodt 2004). The CREEK framework for building knowledge-based systems that integrate CBR with model-based reasoning (MBR) was described more in detail and implemented in the drilling domain (Skalle and Aamodt 2004).

In 2009, Shokouhi and colleagues utilized a newly developed version of CREEK to integrate CBR and MBR (Shokouhi et al. 2009a). In this work static parameters, e.g., Bit Size, along with dynamic parameters, e.g., High ROP (Rate of Penetration) were used. Hole cleaning problems were focused in this research work. To evaluate the case matching process, cases were categorized and labeled with respect to their downtime. It showed that KiCBR improved the retrieval process and increased the accuracy more than case-based reasoning alone. It also presented how to determine the most probable root causes of poor hole cleaning episodes on basis of the knowledge model. They found how integration of MBR and CBR could improve the case matching process. Later, two variants of KiCBR were introduced and compared to other reasoning approaches such as plain CBR and plain MBR. The aim was to obtain the best reasoning approach in terms of the accuracy of the case matching process. The semantic network for the drilling domain was created and all the entities were binary linked. KiCBR tried to expand the set of features in the input cases through the semantic network model. The study showed that the integration of different reasoning methods improved the reasoning better than plain CBR and MBR alone (Shokouhi et al. 2009b).

Aamodt (2006) described the architecture of the DrillEdge system. The DrillEdge system is a commercial technology from Verdande Technology that uses the CBR technique to link real-time data to the past successful experiences. The current version of the system helps to avoid “unwanted events”, i.e., events that lead to a slower drilling progression than expected. The system was tested on historical data from several land-drilling operations in Latin America and excellent results were achieved (Raja et al. 2011). The system was used to predict “Stuck Pipe” and “Lost Circulation” incidents before they occurred. The system produced strong and modest results in stuck pipe and lost circulation situations, respectively. The stuck pipe results show that even in a complex domain, such as drilling, it is feasible to cover a wide set of situations with relatively few cases, as long as they are suitably distributed in the problem space.

4.3 Optimization and execution of drilling process

Optimization of the drilling process is another application of CBR in the drilling industry. A well is being drilled in an efficient way if all the information and knowledge about drilling is utilized. Drilling performance optimization requires all the related knowledge to identify and diagnose barriers to smooth drilling performance.

Milheim and Gaebler implemented an experience transfer tool (heuristic simulation approach) in the oil well drilling domain, based on data sets of 22 actual wells (Millheim and Gaebler 1999). The accumulated data were treated statistically and fitted to a model based on combining human thought, artificial intelligence and heuristic problem solving. The paper presents the methodology through transformation of the 22 sets of well data into a heuristic data set (activated data set). The work has a great potential to be implemented into any geological domain.

Kravis et al. (2002) developed software for assessment of overall well quality. By means of a CBR technique, previous analogous wells or aspects of wells were selected through similarity matching, and adapted to new wells. A comprehensive set of quality measures has been derived and tested on a database containing wells from all over the world.

Perry et al. (2004) describes the development of a case-based knowledge system for drilling performance optimization. A system was designed to represent all pertinent information to be used. Project documents, well summary documents, and technical lesson documents are three levels of documents in the knowledge base hierarchy. The last one, technical lesson documents contain case descriptions where lessons were learned from the analysis of particular drilling experiences. This knowledge-based system enables clients, e.g., engineers, to work smarter by identifying and implementing proven solutions to drilling problems at varying phases; planning, implementation, and post well evaluation.

Recent research on drilling parameters optimization has been conducted in China (Bi et al. 2010; Yuan et al. 2009). A large number of past actual drilling records are used to form a case base of drilling parameters and to establish a knowledge retrieval system by means of data mining technology. They emphasize that drilling parameters collection is inaccurate for many reasons such as measurement and human errors. Noisy data will make it hard to apply the CBR methodology in drilling optimization. To amend an old case and adapt it to new cases, the derivatives repeat method was used. The past amending process was kept as a case which consists of drilling parameters and it is the basis for the new amendment. The system has been tested on a small data set which indicated the feasibility of the CBR on drilling optimization.

4.4 Decision-making

Every decision-making process outputs a final decision option, and requires identification of as many options as possible. Popa et al. (2008) presented a specific application of CBR to determine the optimum cleaning technique for filter failures. These failures occur when unconsolidated reservoir sands flow into a well and cause the pump to become stuck. To correct the situation they needed to decide one out of three problem solving options; bail, washback or foam. The job length and job costs for each method were significantly different. They presented an application of CBR for planning and execution of well interventions, i.e., production operations, in order to improve the decision-making process. In their paper a case-based and a rule-based system were integrated. Rules (IF-THEN statements) were used for adaptation of the most common solution proposed by the CBR system. A large database for reasoning assessment was built. Data from almost 5,000 well interventions over a period of 3 years were collected and analyzed. A small subset of historical cases was taken from the database to evaluate the proposed solution with the actual results. According to the similarity assessment, 80% of the cases were correctly assigned to the successful cleaning method. The system presented by Popa was under development and might now be implemented in the field using the so called revise and retain steps.

Another research work launched by Shokouhi and Skalle (2009) aimed at determination of root causes of poor hole cleaning. Three main parameter groups, each group collectively characterizing a root cause, were identified, and a CBR system was used to select one of the groups given a new problem. Discrimination among these three groups turned out to be a difficult task. The potential success of the method was that the system could improve the decision-making process in an interactive manner by retrieving cases from the correct groups.

4.5 Well integrity

Abdollahi et al. opened a new window for the application of CBR in the petroleum engineering domain. They explained the applicability of CBR for diagnosis of well integrity problems in order to reduce the risk of uncontrolled release of formation fluids into the well through the lifecycle of a well. Well leakages, well control issues and well collisions are named as well integrity. Abdollahi's work focused on well leakages, and was able to identify causes of the leakages versus well activities. Pre-defined rules were used just for determining root causes of the leakage problems. They defined the three most important phases in which well leakages may occur. The three phases are: installation testing, operations (production/ injection), routine testing (in-flow test for BSV and ASV). A causal model was established related to well leakages. 18 cases, 12 solved and 6 unsolved, were built and used in case matching assessment. All the cases were categorized into five groups according to the main cause of leakage. It was shown that pre-defined rules could successfully be integrated with CBR to obtain causes of well leakages (Abdollahi et al. 2008).

4.6 Pattern recognition

In most CBR approaches, an abnormal situation involving loss of process efficiency is triggering the making of a case. It means that whenever a new problem occurs, a case is built and stored in the case database, to be used for the reasoning routine. One of the issues for the case building routine is to determine the severity of problems. One criticism made to CBR is the subjectivity inherent in the case definition. Building cases is a time consuming process. To reduce time, the methodology of a semi-automatic case building and case discrimination process to make a robust case-based reasoning system was introduced and implemented in a recent study (Shokouhi et al. 2010b). In this method all cases, regardless of their severity of problems, are captured. It means that the case database contains diverse cases from high to low risk. It helps to diminish subjectiveness of the case building process. Past cases can be retrieved and evaluated sequentially. As the number of cases increases it is necessary to prioritize which cases should be entered into the case base immediately and which should be stored for later inclusion or be discarded. Shokouhi et al. (2009c) presented an intelligent system for prediction through sequences. As most problems during drilling operation are depth dependent, the system keeps all the cases and the experiences in each defined depth interval to compose sequences of cases. Each sequence is composed of previous, present and next case. The work demonstrated that minor problems might turn into high risk problems later on. The methodology showed its ability through the good prediction results that were about 73%.

5 Applications in other domains of petroleum engineering

Over the last few years CBR has also been applied in other domains of petroleum engineering than drilling. The paper closes with a summary of related work in reservoir engineering, production engineering and petrophysics.

5.1 Applications in reservoir engineering

A standard database search engine returns the results whenever the search criteria meet exactly the matches. A CBR system determines the similarity to seek analogues on the basis of matching attributes that are not exactly similar. Reservoirs characteristics are example of this. In 2002 Bhushan and Hopkinson (Bhushan and Hopkinson 2002) applied CBR to globally search for reservoir analogues as an important step in the planning of new fields. A knowledge sharing tool was developed, called the *Smart Reservoir Prospector* (SRP). The results are accessed in a web-based system. It allows users in any Shell operating unit to access the detailed information in milliseconds. The similarity between reservoirs is computed through a set of attributes. Moreover, using reservoir analogues can provide benefits at all stages of the hydrocarbon exploration and production lifecycle, such as benchmarking scope, sharing knowledge, understanding uncertainties, finding peers, making decision, and applying lessons learned.

5.2 Applications in well completion

A CBR framework was developed by Schlumberger to assess the applicability of seven lift methods (piston pump, jet pump, electric submersible pump, progressive cavity pump, rod pump, multiphase pump for high gas/liquid ratios, and gas lift) for land, platform, and subsea wells (Sinha et al. 2003). It works through decoupling the well design into a high-level or conceptual design phase while allowing for interactions between phases. Similar tools were developed for assessment of other completion methods as well.

5.3 Applications in production

Several intelligent systems were developed for management and control of well production. But none of them were based on the case-based reasoning approach. Instead of CBR, they were just used either model-based or rule-based reasoning approaches. An application of a rule-based system was proposed (Carvalho et al. 2000) for the control of petroleum wells to provide a better control over the operating conditions of wells. This intelligent system was named CONTROL:PCP. The test has been conducted with real field data which validated the designed interface procedure (Morooka et al. 2001; Carvalho et al. 2000).

Two other intelligent systems that were developed for management of well production were published in Portuguese. Later on those systems were briefly described in English by Morooka (Morooka et al. 2001). The first one, WQuest was developed by Milanez et al. (2000) to assist the engineer in the task of water quality evaluation. Linguistic variables are defined and expert knowledge was implemented based on the fuzzy sets method. The second application uses an expert reasoning net which was developed by Mota et al. (1998) to treat water production problems (Mota et al. 1998). In this application, the experts' knowledge was coded in reasoning nets to simulate the expert decision making procedure. The system points out the most probable causes for water production in producing well.

5.4 Applications in Petrophysics

A CBR system coupled with a database system was developed to support the interpretation and classification of new rock samples (Abel et al. 1996). To provide petrographic analyses, the system achieves its reasoning power through the set of previous cases combined with some other source of domain knowledge. Information to build cases was provided through optical and electronic microscope analysis, isotopic and chemical analysis and petrophysics. The system was applied to one type of reservoir rocks i.e., sandstone. An interesting extension of this work would be to interpret other kinds of reservoir rocks. Later on, in 2005, the *PetroGrapher* system was introduced into a real corporate environment (Abel et al. 2005). No wrong conclusions and less than 15% of interpretations missing from complete descriptions of specimens, according to an expert evaluation, showed a real life applicability of high reliability.

6 Summary and conclusion

CBR is a recent methodology compared to many other computer science branches, especially in the oil and gas industry. The paper presents the evolving story of CBR applied to petroleum engineering with a special focus on the drilling branch. According to existing applications, and papers published all over the world, the CBR approach in the petroleum industry is about 15 years old. The results published so far show that the CBR is a proven approach in terms of applicability, compatibility and usability. However, a long-term investment is essential in order to achieve better results and provide a rigorous framework for CBR systems. Figure 3 summarizes the state of the art in CBR applications in petroleum engineering, according to what we have presented in this paper. It also shows that case-based reasoning has been successfully integrated with other reasoning methods such as model-based, rule-based, fuzzy logic, natural language processing and Bayesian networks. The other reasoning modalities are mainly used to improve the feature extraction and the case retrieval processes.

Applications		Researchers		Case-based	Model-based	Rule-based	Fuzzy Logic	Natural Language	Bayesian Network
Drilling	Planning	Irrgang	1999	✓	✓				
		Irrgang et al.	1999	✓	✓				
		Kravis	2002	✓				✓	
		Kravis et al.	2005	✓			✓	✓	
		Morooka et al.	2001	✓			✓		
		Mendes et al.	2003	✓			✓		
	Problem Solving	Skalle et al.	1998	✓	✓				
		Skalle et al.	2000	✓	✓				
		Shokouhi et al.	2009	✓	✓				
		Shokouhi et al.	2009	✓	✓				
		Skalle et al.	2004	✓	✓				
		Aamodt	2006	✓	✓				
		Hamayun et al.	2011	✓					
	Optimization	Milheim et al.	2004	✓					
		Kravis et al.	2002	✓					✓
		Perry et al.	2004	✓					
		Yuan et al.	2009	✓					
		Bi et al.	2010	✓					
	Decision Making	Shokouhi et al.	2009	✓	✓				
		Popa et al.	2008	✓		✓			
	Well integrity	Abdollahi et al.	2008	✓	✓				
	Pattern Recognition	Shokouhi et al.	2010	✓	✓				
Others	Reservoir	Bhushan et al.	2002	✓					
	Completion	Sinha et al.	2003	✓		✓			
	Production	Mota et al.	1998		✓				
		Milanez et al.	2000			✓	✓		
		Carvalho et al.	2000			✓			
	Petrophysics	Abel et al.	1996	✓	✓				
		Abel et al.	2005	✓	✓				

Fig. 3 Integrated reasoning systems implemented in petroleum engineering

The study we have made indicates that Case-based reasoning, particularly when integrated with other reasoning methods, substantially improves human problem solving and decision making.

Acknowledgments The authors would like to express appreciation to people from NTNU and Verdande Technology AS, for their help and cooperation in this work.

References

Aamodt A (2004) Knowledge-intensive case-based reasoning in CREEK. Advances in case-based reasoning, lecture notes in artificial intelligence, LNAI 3155, 7th European Conference, ECCBR 04, Madrid, Springer, August/September, 1–15

Aamodt A (2006) Case-based reasoning for advice-giving in a data-intensive environment. Published in frontiers in artificial intelligence and applications, vol 173. 10th Scandinavian Conference on Artificial Intelligence, 201–205

Aamodt A, Plaza E (1994) Case-based reasoning: fundamental issues, methodological variations, and system approaches. Artif Intell Commun 7(1):39–59

Abdollahi J, Carlsen IM, Randhol P, Tenold E, Haga HB, Jakobsen T (2008) A case-based approach to understand the complexity of causal connections related to well integrity problems. SPE 111129-MS, IADC/SPE Drilling Conference, Orlando, Florida, USA, 4–6 March

Abel M, Reategui EB, Castilho JMV (1996) Using case-based reasoning in a system that supports petrographic analysis. Artificial intelligence in the petroleum industry: symbolic and computational applications II, chapter 7, Éditions Technip, Paris, France, pp 159–172. In: Braunschweig, B, Brendal B (eds)

Abel M, Silvaa LAL, Campbell JA, De Rosc LF (2005) Knowledge acquisition and interpretation problem-solving methods for visual expertise: study of petroleum-reservoir evaluation. J Petroleum Sci Eng 47(1–2):51–69

Bi X, Wang J, Feng J, Sun S (2010) Research on drilling parameters optimization based on case-based reasoning. Seventh International Conference on Fuzzy Systems and Knowledge Discovery (FSKD-10)

Bhushan V, Hopkinson SC (2002) A novel approach to identify reservoir analogues. European Petroleum Conference, Aberdeen, United Kingdom, 29–31 October

Carvalho PG, Morooka CK, Bordalo SN, Guilherme IR (2000) CONTROL PCP: an intelligent system for progressing cavity pumps. SPE 63048, Annual Technical Conference, Dallas, 1–4 October

Cunningham P (2008) A taxonomy of similarity mechanisms for case-based reasoning. University College Dublin, Technical Report UCD-CSI-2008-01

Finnie G, Sun Z (2002) Similarity and metrics in case-based reasoning. Int J Intell Syst 17(3):273–287

Irrgang R, Damski C, Kravis S, Maidla E, Millheim K (1999a) A case-based system to cut drilling costs. SPE 56504, SPE Annual Technical Conference and Exhibition held in Houston, Texas

Irrgang R, Kravis S, Agawani M, Maidla E (1999b) Automated storage of drilling experience: capture and re-use of engineering knowledge. Petroch, New Delhi, India, 1–6

Kolodner J (1992) An introduction to case-based reasoning. Artif Intell Rev 6:3–34

Kolodner J (1993) Case-based reasoning. Morgan Kaufmann, San Francisco

Koton P (1988) Reasoning about evidence in causal explanations. In: Proceedings of the seventh national conference on artificial intelligence (AAAI-88). AAAI Press, Menlo Park, California, pp 256–261

Kravis S, Irrgang R (2005) A case based system for oil and gas well design with risk assessment. Appl Intell 23(1):39–53

Kravis S, Irrgang R, Phatak A, Martins A, Nakagawa E (2002) Drilling parameter selection for well quality enhancement in deepwater environments. SPE 77358-MS, SPE Annual Technical Conference and Exhibition, San Antonio, 29 Sep. 2 Oct

Mark WS (1989) Case-based reasoning for autoclave management. In: Proceedings of the case-based reasoning workshop

Marling C, Rissland E, Aamodt A (2005) Integrations with case-based reasoning. Know Eng Rev 20(03):241–245

Mendes JRP, Guilherme IR, Morooka CK (2001) Case-based system: indexing and retrieval with fuzzy hypercube. Joint 9th IFSA World Congress and 20th NAFIPS International Conference, Vancouver

Mendes JRP, Morooka CK, Guilherme IR (2003) Case-based reasoning in offshore well design. J Petroleum Sci Eng 40:47–60

Milanez VA, Morooka CK, Guilherme IR, Mendes JRP (2000) Intelligent system to define parameters for injection water in reservoirs. Rio Oil & Gas Expo and Conference, Rio de Janeiro- Brazil, 16–19 October. (in Portuguese)

Millheim KK, Gaebler T (1999) Virtual experience simulation for drilling—the concept. SPE 52803-MS, SPE/IADC Drilling Conference, Amsterdam, 9–11 March

Morooka CK, Guilhermeb IR, Mendesa JRP (2001) Development of intelligent systems for well drilling and petroleum production. J Petroleum Sci Eng 32(2–4):191–199

Mota RO, Ferreira LEA, Rocha RPSMV, Rebello AF (1998) Expert system for management of petroleum reservoirs. Rio Oil & Gas Expo and Conference, Rio de Janeiro-Brazil, 5–8 October (in Portuguese)

Perry PB, Curry DA, Kerridge JD, Lawton J, Bowden D, Flett AN (2004) A case based knowledge repository for drilling optimization. SPE 87994-MS, IADC/SPE Asia Pacific Drilling Technology Conference and Exhibition, Malaysia, 13–15 September

Popa A, Popa C, Malamma M, Hicks J (2008) Case-based reasoning approach for well failure diagnostics and planning. SPE 114229-MS, SPE Western Regional and Pacific Section AAPG Joint Meeting, Bakersfield, California, USA, 29 March-2 April

Raja H, Sørmo F, Vinther ML (2011) Case-based reasoning: predicting real-time drilling problems and improving drilling performance SPE 141598, SPE Middle East Oil and Gas Show and Conference held in Manama, Bahrain, 6–9 March

Schank RC (1982) Dynamic memory: a theory of reminding and learning in computers and people. Cambridge University Press, New York

Schank RC, Abelson RP (1977) Scripts, plans, goals and understanding. Erlbaum, Hillsdale, New Jersey, US

Shokouhi SV, Skalle P (2009) Enhancing decision making in critical drilling operations. SPE 120290, SPE Middle East Oil & Gas Show and Conference held in the Bahrain, 15–18 March

Shokouhi SV, Aamodt A, Skalle P, Sørmo F (2009a) Determining root causes of drilling problems by combining cases and general knowledge. Lecture Notes in Computer Science, vol 5650, Springer, pp 509–523 ISSN-0302-9743

Shokouhi SV, Aamodt A, Skalle P, Sørmo F (2009b) Comparing two types of knowledge-intensive CBR for optimized oil well drilling. In: Proceedings of the 4th Indian International Conference on Artificial Intelligence (IICAI-09), Tumkur India, December 16–18, pp 722–737

Shokouhi SV, Aamodt A, Skalle P, Sørmo F (2009c) Integration of real-time data and past experiences for reducing operational problems. IPTC 13969, Proceedings of the International Petroleum Technology Conference held in Doha, Qatar, 7–9 December

Shokouhi SV, Aamodt A, Skalle P (2010a) Applications of CBR in oil well drilling. In: Proceedings of IIP2010—6th international conference on intelligent information processing. IFIP Conference Series. Manchester, UK, October 13-16. Springer, pp 102–111

Shokouhi SV, Aamodt A, Skalle P (2010b) A semi-automatic method for case acquisition in CBR, a study in oil well drilling. In: Proceedings of the tenth IASTED international conference on artificial intelligence and applications, AIA-10,ACTA Press, Innsbruck, Austria, February 15–17, 2010, pp 263–270

Sinha S, Yan M, Jalali Y (2003) Completion architecture: a methodology for integrated well planning. SPE 85315-MS, SPE/IADC Middle East Drilling Technology Conference and Exhibition, Abu Dhabi, United Arab Emirates, 20–22 Oct

Skalle P, Aamodt A (2004) Knowledge-based decision support in oil well drilling. In: Proceedings of the ICIIP, international conference on intelligent information systems, Beijing, 21–23 October

Skalle P, Aamodt A, Sveen J (1998) Case-based reasoning, a method for gaining experience and giving advise on how to avoid and how to free stuck drill strings. In: Proceedings of IADC middle east drilling conference, Dubai, November

Skalle P, Sveen J, Aamodt A (2000) Improved efficiency of oil well drilling through case-based reasoning. In: Proceedings of PRICAI 2000, sixth pacific rim international conference on artificial intelligence, Melbourne, Aug–Sept

Watson I, Marir F (1994) Case-based reasoning: a review. Knowl Eng Rev 9(4):355–381

Whitley D (1994) A genetic algorithm tutorial. Stat Comput 4(2):65–85

Yuan P, Yan T, Feng J, Chang, L (2009) Application of case-based reasoning method on drilling parameter optimization. Proceedings of the CiSE, international conference on computational intelligence and software engineering, Wuhan, China, 11–13 December

Zadeh LA (1965) Fuzzy sets. Inf Control 8(3):338–353