Journal of Petroleum Science and Engineering 138 (2016) 245–252

Contents lists available at ScienceDirect

Journal of Petroleum Science and Engineering

journal homepage: www.elsevier.com/locate/petrol

A structured approach for the diagnosis of formation damage caused by organic scale deposits and surface active agents, Part II: Expert system development

Abdullah S. Ebrahim [a,*], Ali A. Garrouch [a], Haitham M.S. Lababidi [b]

[a] Petroleum Engineering Department, Kuwait University, PO Box 5969, Safat 13060, Kuwait
[b] Chemical Engineering Department Kuwait University, PO Box 5969, Safat 13060, Kuwait

ARTICLE INFO

Article history:
Received 11 July 2015
Received in revised form
27 October 2015
Accepted 28 October 2015
Available online 31 October 2015

Keywords:
Formation damage
Fuzzy expert system
Artificial intelligence
Emulsions
Wettability reversal
Water blocks
Organic scale Deposits
Wax and asphaltene

ABSTRACT

This paper (Part II) reports on the development of a Formation Damage Expert System (FODEX) for aiding in the preliminary diagnosis of formation damage types that consist of emulsions, water blocks, wettability reversal and the deposition of asphaltenes and wax in hydrocarbon reservoirs. The reasoning process is based on compiled rules that have been arranged in decision trees constructed using knowledge derived from standard industrial practices integrated with empirical models to assure vigorous expert opinion. The structured approach for formation damage diagnosis has been detailed in Part I of this work. FODEX automates the reasoning process embedded in the decision trees using logic blocks represented as four modules. Fuzzy logic has been used in handling incomplete and conflicting knowledge encountered in determining the likelihood of asphaltene and wax deposition. The developed formation damage expert system has been tested with three documented field cases of producing wells in the Rangely, Typhoon, and Magwa–Marrat oil reservoirs. FODEX decisions regarding the type of damage inflicted on these fields have been validated with compositional PVT simulation software. The expert system made a thorough diagnosis of damage types, in agreement with PVT simulations, field observations, PVT cell testing and special core analysis.

1. Introduction

Formation damage is defined as any mechanism that reduces the relative permeability to oil or gas in the formation. Types of formation damage caused by organic scale deposition and by rock–crude interaction with surface active agents can occur at all stages of reservoir development (Garrouch et al., 2006; Garrouch and Malallah, 2007). These damage types not only reduce the rock transmissibility but also degrade the flow assurance capabilities and cause significant financial losses (Garrouch and Al-Ruhaimani, 2005). Indeed, intervention and remediation costs are very expensive, especially for deep-water sub-sea reservoirs that may be distant from the host platforms. Remediation operations may require intense chemical solvent soaking operations that are likely to have a detrimental impact on health, safety, and the environment. Incorrect remediation decisions caused by false diagnosis will increase the operational costs tremendously and are likely to complicate the efforts of adequate field development. The process of damage diagnosis is a lengthy and complex endeavor that relies heavily on expertize and human judgment, which are usually scarce and not readily available. Such diagnostic tasks may be better managed, if automated.

Artificial intelligence (AI) techniques enable the development of more intelligent applications that are capable of emulating the reasoning process of human experts and that involve impressions, uncertainty and vagueness. They have been increasingly used in the oil and gas industry to enhance operational performance, production and recovery and reduce diagnostic and intervention costs and environmental and safety risks (Ahmadi and Golshadib, 2012; Ahmadi and Ebadi, 2014; Ahmadi and Bahadori, 2015). Such applications are much needed and have gained wide acceptance in the upstream oil industry. They include smart wells (Yeten et al., 2004; Van der Poel and Jansen, 2004; Al-Anazi and Babadagli, 2010), intelligent reservoir characterization (Nikravesh and Aminzadeh, 2001) and online analysis and visualization of log data (Mohaghegh, 2011; Liu et al., 2014).

Expert systems or *knowledge-based systems* are AI programs that achieve expert-level competence in solving problems by representing and handling knowledge used by human experts. *Fuzzy*

* Corresponding author.
E-mail address: aebrahim75@hotmail.com (A.S. Ebrahim).

http://dx.doi.org/10.1016/j.petrol.2015.10.037
0920-4105/

logic is usually integrated in the reasoning process for handling uncertain and vague knowledge. The main attractive feature of *fuzzy expert systems* is the handling and manipulation of linguistic variables (such as ‘high,’ ‘low,’ etc.), which are commonly used by human experts (Lababidi and Baker, 2003).

A number of expert system applications have been reported in the literature of various petroleum engineering disciplines, including the selection and design of EOR processes (Gharbi, 2000; Eghbali et al., 2015), exploration (Schrader et al., 2009), and drilling (Garrouch and Lababidi, 2001; Garrouch et al., 2005). Sheremetov et al. (2008) developed “Smart-Drill,” a fuzzy expert system for diagnosing and solving lost circulation problems. Bartko et al. (1996), and Nitters et al. (2000) integrated fuzzy rules with mathematical models to develop a structured expert system for damage diagnosis and treatment selection. Xiong and Holditch (1995) presented a comprehensive fuzzy expert system to diagnose formation damage and to allocate appropriate treatment. Despite the fact that there are a number of useful applications reported in the literature, developed systems are not yet openly or commercially available. This is mainly due to confidentiality issues and the fact that the expertize that has been gained over the years is invaluable and should be kept at a corporate level.

The objective of this study is to develop an expert system for automating the diagnosis of formation damage types related to organic scale deposits and surface-active agents (FODEX). FODEX is based on the knowledge derived from standard industry practices. Part I of this work provides a detailed description of the knowledge and the reasoning procedure needed to diagnose formation damage caused by organic scale deposits. The domain specific knowledge is made available for researchers in this field for further research and development in the future. First, the structure of FODEX will be explained, then the implementation of the expert system will be outlined, and finally the expert system will be tested against a number of actual field cases.

2. Expert system structure

The development of the formation damage expert system (FODEX) was carried out in four main stages: (a) knowledge acquisition, (b) knowledge representation, (c) expert system development, and (d) system testing and validation. The knowledge acquisition stage involved gathering information from the literature and, most importantly, conducting a series of working sessions with experts in the field. Elicited knowledge was recorded, refined and structured in decision trees. Decision trees were found to be a very effective knowledge representation method and proved vital during all development stages. They were considered the main reference and communication means between the experts and the system developers. Moreover, they facilitate maintaining, modifying and extending the logic of the system.

The structure of FODEX is illustrated in Fig. 1 of manuscript Part I of this series. This structure is based on four logic blocks corresponding to the knowledge modules represented as decision trees in Part I of this work. A diagnostic session starts by processing

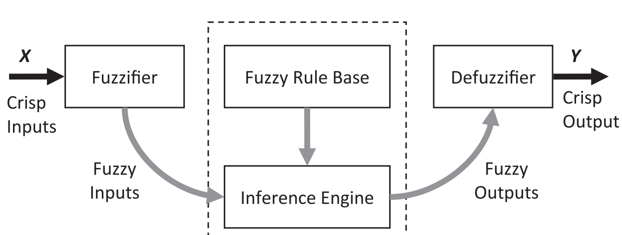

Fig. 1. Simplified structure of a fuzzy system.

Module I to discern external damage from actual formation damage. If formation damage exists, the remaining three modules (II, III and IV) are activated simultaneously to diagnose the type of formation damage. Otherwise, the system would recommend fixing a peripheral skin problem, mechanical problem or cleaning the wellbore.

Module II specializes in diagnosing the potential of asphaltene deposition. The main outcome of this module is the determination of the likelihood of asphaltene deposition. The reasoning process estimates the propensity of asphaltene deposition using a set of rules of thumb, which were extracted from experts working in this area (Lababidi et al., 2004). As described below, this particular module uses fuzzy logic in representing and processing the rules of thumb. Decisions are also based on the rules derived from the colloidal instability index as well as flooding and acid-induced sludge criteria. Similarly, Module III is used for assessing the potential of wax deposition, whereas Module IV is used for diagnosing damage caused by emulsions, water blocks, and wettability reversal.

3. Expert system development

The two principal components of an expert system are the *knowledge base* and the *inference engine*. The knowledge base contains factual and heuristic knowledge, which is represented as facts and rules to be used by the inference engine to perform the reasoning process and arrive at a conclusion. The most common form of knowledge representation is the IF-THEN rule-based expressions of the type:

$$IF\ conditions\ (antecedents),\ \ THEN\ conclusions\ (consequents) \tag{1}$$

This form typically states that given a set of facts (the conditions, hypothesis, or antecedent), one can infer, or derive, other facts called conclusions (consequents). Rules are grouped in *rule sets*. The knowledgebase structure of FODEX consists of a number of independent rule sets, each dedicated to a specific reasoning and decision-making task. Each of the four modules, given as decision trees in part I of this work (see Fig. 1 in Part I manuscript), is represented as one or more rule sets. Using rule sets proved to be effective during the development of the expert system and enabled good flexibility for introducing changes as well as for extending the capabilities of the system.

Based on the interaction with the user and data derived from various sources, such as databases and computational procedures, the overall reasoning process may arrive at multiple possible conclusions and recommendations, in the same way human experts would. The reasoning process may handle this issue by assigning a degree of certainty to the conclusions of the rules. In addition, the inference engine applies a predefined mechanism to determine the overall confidence associated with each recommendation. In the current implementation of FODEX, degrees of certainty and overall confidences are assigned values ranging from 0, meaning absolutely certain to be not valid, to 1, meaning absolutely certain to be valid. As explained below, for specific rule sets, fuzzy logic was used in assigning and deriving the degrees of certainty. Confidence values are combined and updated using the following formula:

$$C_{updated} = C_{new} + \left[C_{old} \times \left(1 - C_{new}\right)\right] \tag{2}$$

For example, combining the two confidence values $C_{old}=0.3$ and $C_{new}=0.6$ results in $C_{updated}=0.6+(0.3\times(1-0.6))=0.72$.

Exsys Corvid (Exsys Inc, 2010) was used in the implementation of the Formation Damage Expert System (FODEX). Exsys Corvid is an object-oriented expert system development software that