Knowledge Representation Model and Decision Support System for Enhanced Oil Recovery Methods

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***Abstract*—**In this paper we develop decision support system for enhanced oil recovery methods selection. Fuzzy production rules were suggested to describe expert's knowledge. We use various types of constraints in fuzzy production rules, and expert estimates an importance rate of these constraints. We suggest fuzzy inference method for decision support system with the proposed fuzzy production rules. Fuzzy inference method is capable to work in conditions of gaps in the source data. We used the decision support system to select enhanced oil recovery methods on some oil fields.

***Keywords*—**Decision support systems, Fuzzy logic, Enhanced oil recovery.

I. Introduction

NOWADAYS, oil production is the major factor of the economy of many countries, including Russia. About 20% of Russia's GDP comes from oil production. Under these circumstances, federal governments pay great attention to an effective oil production.

It is hard to discover new giant oil fields. Actually, at the present time, main efforts in the oil production are concentrating on the oil recovery from the existing oil fields. Unfortunately, many countries, including Russia, have a lot of depleted oil fields. It is impossible to effectively use primary oil recovery methods in such situations, thereby secondary and tertiary recovery methods become very popular. These methods also referred to as enhanced oil recovery (EOR) methods [1]. There currently are a lot of different EOR methods including steam, water injection, CO_2 injection, polymer flooding, microorganisms injection etc [2].

Using EOR methods makes it possible to dramatically increase amount of crude oil that can be extracted from the oil field. Primary oil recovery methods produce about 10% of original oil from the reservoir, whereas EOR methods increase this amount up to 60% or more [3].

Generally, EOR methods selection is doing by experts. They are taking into account specific conditions of oil production. However, experts face some difficulties during this selection, they have to consider a lot of special features and constraints under this selection;

- fuzzy character of most constraints;
- a large amount of EOR methods nowadays;
- a large number of gaps in the source data.

Some artificial intelligence approaches are using to make decisions under these strong circumstances. In [4]-[5] neural networks are suggested for selection and evaluation of EOR methods. Possibility of using expert systems to decide this task was considered in [6]-[8]. EOR methods selection with using Bayesian network was considered in [9].

Expert systems and decision support systems provide effective mechanisms for deciding various tasks under represented difficulties. In [10] rule-based expert system written in PROLOG has been suggested. This expert system assists in selection complex petroleum recovery processes. In [11] expert system has been suggested with possibility of changing and editing the parameters of EOR methods. Fuzzy expert system for EOR project risk analysis was presented in [12]. Ontology driven decision support system was presented in [13].

In this paper we developed Decision Support Systems (DSS) with fuzzy logic for EOR methods selection. This DSS makes it possible for expert to define fuzzy constraints, works with gaps in the source data. DSS also includes reference system about EOR methods and explanation block that allows using DSS for training inexperienced users.

II. Knowledge representation in decision support system

We suggest knowledge representation model for decision support system in the form of following fuzzy if-then rules:

Rule R^j

IF

$$P_1^j \quad is \quad A_1^j \quad \left(w_1^j\right)$$

AND

$$P_2^j \quad is \quad A_2^j \quad \left(w_2^j\right)$$

…

AND

$$P_{s_j}^j \quad is \quad A_{s_j}^j \quad \left(w_{s_j}^j\right)$$

THEN

IT IS POSSIBLE TO USE EOR METHOD T^j $[CF^j]$, (1)

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where $P_i^j \in P$ - parameter that defines specific conditions for the oil field or oil well (such as water cut of crude oil, reservoir pressure etc), A_i^j - crisp or fuzzy constraint for the parameter P_i^j, w_i^j - weight that determines the importance of the parameter P_i^j in the rule R^j, CF^j – certainty factor for the rule R^j that is defined by expert, T^j – EOR method.

We use following types of the parameters $P_i \in P$.

- type "List of values" defines parameter P_i with discrete set of values S_i;
- type "Numeric" defines parameter on the numerical interval $[a_i,b_i] \subset R$;
- type "Linguistic variable" defines parameter as a linguistic variable with fuzzy values.

We use following types of the constraints A_i for the parameters $P_i \in P$.

1. Crisp constraints:

1.1. $A_i = \{s_{ik}\}$ for the parameter P_i defined as "List of values", $s_{ik} \in S_i$ are possible values for the parameter P_i

1.2. $A_i = \bigcup [a_{ik}, b_{ik}] \subset [a_i, b_i]$ for parameter P_i defined as "Numeric".

1.3. $A_i = \bigcup L_{ik}, L_{ik} = [a_{ik}, b_{ik}] \subset R$ for parameter P_i defined as "Linguistic variable". Linguistic value N_{ik} associates with the interval $L_{ik} = [a_{ik}, b_{ik}]$.

2. Fuzzy constraints:

We define fuzzy constraints in (1) by fuzzification of the crisp constraints (1.2) and (1.3) with using fuzzy linguistic modifiers.

Let $[a,b]$ be a crisp interval. We transform it to trapezoidal fuzzy number defined by quartlet (2).

$$(a - a \cdot m, a, b, b + b \cdot m), \quad (2)$$

where m is the fuzzification coefficient.

We define fuzzification coefficient m with using following fuzzy linguistic modifiers (see Table I).

TABLE I
FUZZY LINGUISTUC MODIFIERS

Fuzzy linguistic modifier	Fuzzification coefficient m
NEARLY	0.05
ABOUT	0.1
APPROXIMATELY	0.25
ROUGHLY	0.5

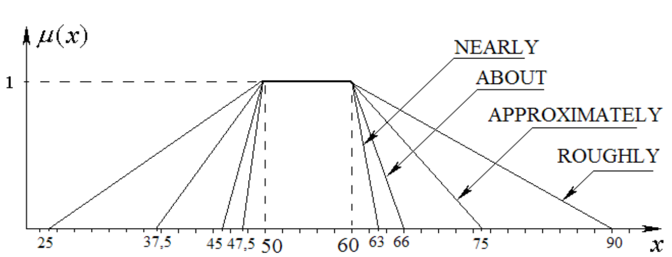

Fig. 1 Defining fuzzy constraints

Fig. 1 shows an example of defining fuzzy constraints with using fuzzy linguistic modifiers.

Weights w_i in (1) are defined as integers 1,2,3,4,5,6 and can be interpreted as linguistic values. Expert defines these values with using qualitative scale (see Table II).

TABLE II
QUALITATIVE SCALE FOR DEFINING IMPORTANCE RATE OF THE CONSTRAINTS

Linguistic category	Weight w_i
Least important	1
No very important	2
Moderately important	3
Important	4
Very important	5
Extremely important	6

For example, we can define rule (1) for decision support system by following way.

IF

Formation is "Devonian" (Very important)

AND

Bottom hole pressure is ABOUT ([0;1190] PSI) (Least important)

AND

Water cut of the crude oil is APPROXIMATELY [0;60] (Important)

AND

Decreasing of flow efficiency is ABOUT [15%;100%] (Least important)

AND

Reservoir pressure is ABOUT ([12;60] MPa) (Moderately important)

AND

Oil production rate is ABOUT ([0,27l;max] barrel/day) (Moderately important)

AND

Well type is "Production" (Least important)

AND

Capacity of the oil reservoir is (ABOUT (MODERATE) ∪ ABOUT (BIG) (Important)

THEN

IT POSSIBLE TO USE vibrowave depression-chemical impact [CF=0.9]

III. FUZZY INFERENCE IN DECISION SUPPORT SYSTEM

Fuzzy inference block in DSS receives information about specific conditions of oil production on the specific oil well and provides the recommendations about possibility of using specific EOR methods at these conditions. Fig. 2 shows structure of the fuzzy inference block in DSS.

Knowledge base stores the rules that are defined by experts in the form (1).

We implement backward chaining, goal-driven search in DSS. Thereby, *rules' selection block* hypothesizes and selects concrete rules from the knowledge base with EOR method T^j in the consequent.

Rule's parsing block parsers selected rules and gets elementary constraints from the antecedents.

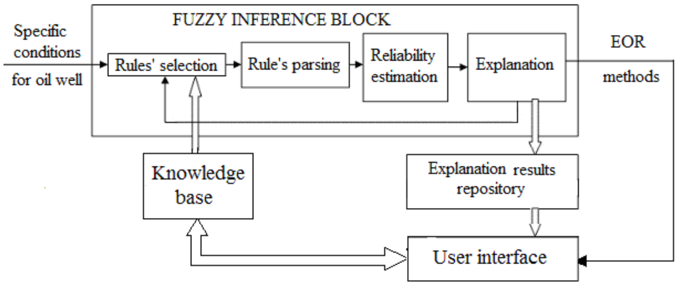

Fig. 2 Structure of the fuzzy inference block

Reliability estimation block analyzes constraints and assesses firing level, confidence degree and reliability for every rule. It also assesses reliability for every EOR method T^j and recommends the best method for applying. It is possible to make decisions under a large number of gaps in the source data.

Explanation block makes a detail explanation about how the decision was made. It also puts this detail information into *explanation results repository*. Inexperienced users can use this repository for their training of making the best decisions.

Let's consider in detail how reliability estimation block works.

Let we have specific conditions for the oil well. These conditions determine specific values for the parameters $P_i \in P$. Further, we can select specific rules for these conditions. Let's define reliability level RL for the rule R by using (2).

$$RL(R)=F \cdot D \cdot CF, \tag{2}$$

Where, F is the firing level , D is the confidence degree , CF is the certainty factor for the rule R that is defined by (1).

Firing level F for the rule R is defined by (3)

$$F = \frac{\prod_{i=\overline{1,k}} f_i \cdot w_i}{\prod_{i=\overline{1,k}} w_i}, \tag{3}$$

Where, $f_i \in [0;1]$ is a firing level for the constraint A_i in the rule R, w_i is a weight for the constraint A_i. Value k is the number of the constraints in the rule R, where parameter P_i is defined.

Firing level f_i for the constraint A_i with defined parameter P_i is estimated as membership value of P_i in constraint A_i. In the case of crisp constraint A_i, $f_i \in \{0;1\}$. In the case of fuzzy constraint A_i, $f_i \in [0;1]$.

Confidence degree D for the rule R is calculated by using (4)

$$D = \frac{\sum_i w_i}{\sum_j w_j}, \tag{4}$$

Where, $w_i, i=\overline{1,k}$ are weights for the constraints A_i for which parameter P_i is defined, $w_j, j=\overline{1,s}$ are weights for the complete set of constraints A_j in the rule R.

There is a one feature of fuzzy inference block in DSS. It estimates reliability level for the rule R only if complete set of the parameters P_i with extremely important restriction is defined. Otherwise value RL=0.

Let $\{R^j\}$ be the set of the rules which estimate possibility of using EOR method T. We will estimate reliability level for the method T by using (5).

$$RL(T) = \max_j RL(R^j) \tag{5}$$

Fuzzy inference block (FIB) using following algorithm for decision making.

Decision making algorithm

Step 1. FIB selects next rule R^j from the knowledge base. If all rules have been reviewed then go to step 9.

Step 2. FIB suggests a hypothesis on using EOR method T^j from the consequent of the rule R^j.

Step 3. FIB is checking in the rule R^j if there are exist some undefined parameters with extremely important restriction (w_i=6). If there are exist then FIB asks user to define their values. If user can't define any values, then FIB goes to select next rule (step 1).

Step 4. FIB estimates firing level F^j for the rule R^j by using (3).

Step 5. FIB estimates confidence degree D^j for the rule R^j by using (4).

Step 6. FIB gets certainty factor CF^j for the rule R^j from the knowledge base.

Step 7. FIB estimates reliability level RL^j for the rule R^j by using (2). FIB includes couple (T^j,RL^j) in the data base if RL^j>0.

Step 8. FIB selects next rule (go to the step 1).

Step 9. FIB analyzes data base. If there are exist several couples (T^j,RL^j) for the EOR method T^j, then FIB estimates reliability level for the method T by using (5).

Step 10. FIB produces the result as set of couples (T^j,RL^j), where T^j is the EOR method, RL^j is the corresponding reliability level.

The big advantage of estimating the confidence degree D is possibility to make decisions under large number of gaps in the source data. Expert would use confidence degree values to make better decisions about best EOR method.

FIB uses explanation block to make explanation results repository. Expert would also use this repository to make better decisions. We can use explanation block and explanation results repository for testing existing rules. Moreover, inexperienced users can use explanation results repository for their training. To decide these tasks, explanation block stores following information in the repository:

- firing levels f_i for all constraints A_i and all rules R;
- undefined parameters P_i for all rules R.

IV. DSS CONSTRUCTOR "OILRULE"

We developed software for designing decision support systems which select enhanced oil recovery methods. This software was called DSS constructor "OilRule".

DSS constructor includes following general GUI modules:

- KB constructor;
- oil wells reference system;
- FIB & explanation block GUI;

KB constructor is a GUI for developing knowledge bases for selection enhanced oil recovery methods. Expert works with the following references in this GUI.

- Parameters reference GUI (see Fig. 3). Expert uses this reference to define complete set of the parameters *P* and their types: "List of values", "Numeric", "Linguistic variable".

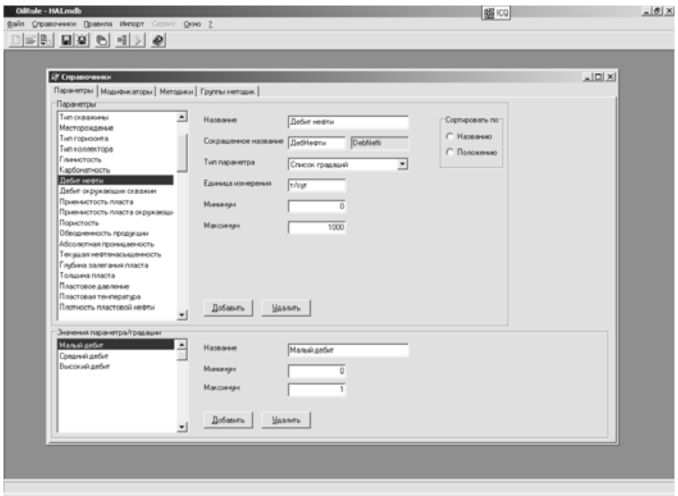

Fig. 3 Parameters reference GUI

- EOR methods reference GUI (see Fig. 4). Expert uses this reference to define complete information about EOR method. User uses this reference to get complete information about some EOR method. Also user uses it to select possible oil wells for concrete EOR method.

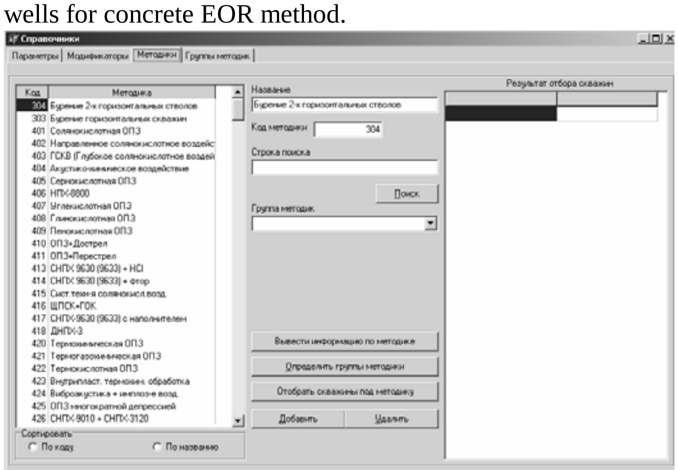

Fig. 4 EOR methods reference GUI

- Rule reference GUI (see Fig. 5). Expert uses this reference to define rules in form (1). Thereafter fuzzy inference block uses these rules to make a decision about possible EOR methods. When defining a rule, expert uses parameters from "Parameters reference" and defines crisp or fuzzy constraints for them.

Expert uses oil wells reference system GUI (see Fig. 6) to define parameters' values for specific oil wells. Expert defines these values manually or by using import wizards from such well-known Russian systems as "InnerGaze" or "Lazurit". Expert also can use this GUI for primary oil well's selection by using simple filters. Later, fuzzy inference block would be used to select EOR method for the remaining oil wells.

User uses FIB & explanation block GUI (see Fig. 7) to select possible EOR methods for some oil wells and to get detail information about fuzzy inference. User can get access to explanation results repository and get information about firing levels f_i for each constraint, about F,D,CF values for each rule.

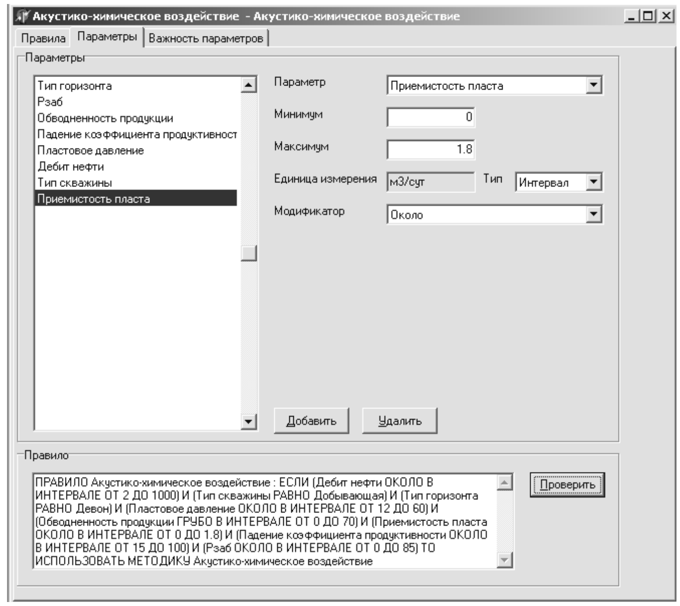

Fig. 5 Rule reference GUI

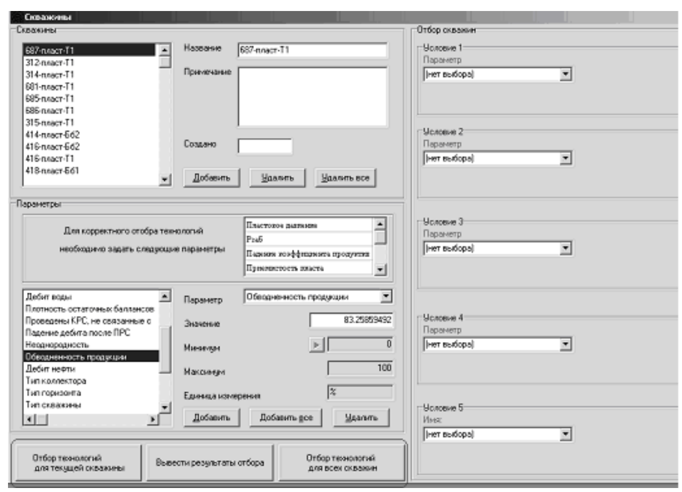

Fig. 6 Oil wells reference system GUI

V. Experimental Results

Decision support system includes 74 parameters, 79 rules for 52 EOR methods.

For example, we used DSS for EOR methods selection on "Feofanovskoye" oilfield for LUKOIL Company. There were some gaps in the source data. For some circumstances, we didn't know values of following parameters:

- reservoir pressure;
- bottom hole pressure;

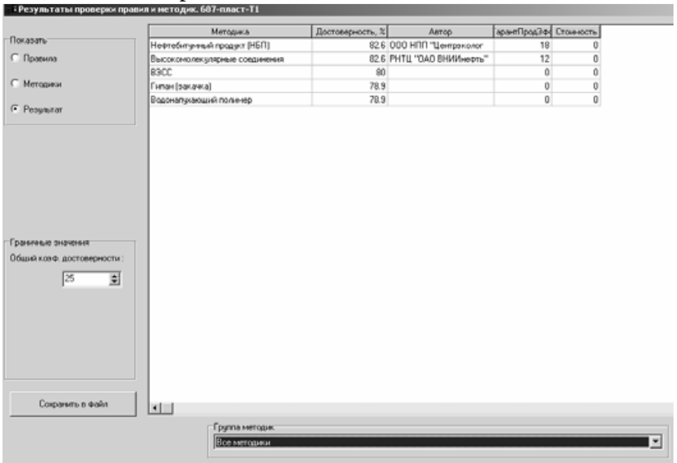

Fig. 7 FIB & explanation block GUI

- oil production rate;
- capacity of the oil reservoir.

Table III shows an example of selection EOR methods for oil well N 1.

TABLE III
SELECTION EOR METHODS FOR OIL WELL N 1

No	EOR method	Reliability level
1	Directed hydrochloric acid exposure	1
2	DISIN+HCl	1
3	Oil bituminous product	0.826
4	High-molecular compound	0.826
5	VESS	0.8
6	GIPAN	0.79
7	Water swellable polymer	0.79

Table IV shows an example of selection EOR methods for oil well N 2.

TABLE IV
SELECTION EOR METHODS FOR OIL WELL N 1

No	EOR method	Reliability level
1	SNPH-9010	1
2	Scrid	1
3	KNN	1
5	Hydrochloric acid deep impact	1

These results completely agreed with the opinion of experts.

VI. CONCLUSION

In this paper we suggested knowledge representation model in form of fuzzy if-then rules with weights of the constraints. We used this model for expert's knowledge representation about selection of EOR methods, but fields of application of this model are not limited by oil production. This knowledge representation model and fuzzy inference scheme can be used for decision making in various applications, such as medicine, geology etc. The major advantage of this model is possibility to use fuzzy constraints with weights and work under large number of gaps in the source data.

We can use "OilRule" to construct decision making systems for various applications.

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