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Neurofuzzy Model of Formation of Knowledge Bases for Selection of Geological and Technical Measures in Oil Fields

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Abstract

This paper poses and solves the problem of developing the up-to-date neuro-fuzzy model of formation of a knowledge base for an intelligent decision-making support system for selection of geological and technical measures in oil fields. The analysis of the traditional approach to the formation of fuzzy knowledge bases made it possible to reveal its shortcomings associated with the need to attract experts, structure and formalize the system of decision-making rules by them. This process is laborious and does not always provide an acceptable result. To eliminate the disadvantages of the traditional approach, we proposed an approach to the automatic formation of a knowledge base based on the construction of a neuro-fuzzy model of a collective of fuzzy neural networks. We formulated the requirements in view of the formed fuzzy rules. We developed a scheme for using the rules of the knowledge base to solve the problem of selecting geological and technical measures in oil fields. We tested the generated knowledge base on the example of solving the problem of selecting geological and technical measures for various wells of the Feofanovskoye Field. Application of the knowledge base made it possible to select a list of optimal measures for given wells. The experiment results are satisfactory and are confirmed by the positive expert assessments, selecting geological and technical measures at this field.

Keywords- Neuro-Fuzzy Model, Knowledge Base, Geological And Technical Measures, Oil Field, Decision-Making Support

I. INTRODUCTION

Currently, artificial intelligence technologies are being actively introduced to solve practical problems in various subject areas of human activity [1-5]. One of these areas is the oil industry, for which it is important to solve a number of problems to increase the oil field development efficiency [6-8]. The task of selecting geological and technical measures (GTM) to enhance oil recovery is urgent in this subject area [9].

The solution to this problem is accompanied by a number of difficulties. The main ones are possible fuzziness, uncertainty and incompleteness of knowledge about the studied field [10].

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Under these conditions, it is very difficult to effectively use traditional methods of mathematical statistics, probabilistic approaches and hydrodynamic equations.

To solve the problem of selecting GTM in the oil fields, it is advisable to use intelligent decision-making support systems (DSS) [11-13] based on the fuzzy logic methods and fuzzy inference algorithms [14]. Such systems, due to the knowledge of experts accumulated in them, make it possible to recommend a decision-maker (DM), rational in the current conditions of GTM [15]. At the same time, the proposed solution is interpretable and understandable for a person, which increases its reliability and confidence level among the DM. The knowledge base used in this case can be formed by an expert method [16, 17], or the process of its formation can be automated [18, 19]. In the latter case, it is currently relevant to use Data Mining methods to form fuzzy knowledge bases [20-22]. As the data analysis tool, it is relevant to use a neuro-fuzzy model formed as a result of training a fuzzy neural network (FNN) [23]. At the same time, the model, having been trained on the initial data characterizing the oil field and specific production wells, will make it possible to form a fuzzy knowledge base for the GTM selection.

II. METHODS

In any decision-making support system, its main component is the knowledge base [24]. At the same time, an approach with the involvement of experts is implemented to form a knowledge base in most of the existing expert systems in various subject areas, in particular in the oil industry [10, 16].

For example, the work [7] proposes the methods for solving the problem of developing recommendations on the GTM appointment. The practical use of the approach made it possible to form a knowledge base that includes many rules of the following type:

IF the horizon type is "Devon" AND the period Rzab<Rnas is more than 0.5 years AND the water cut is CLOSE ([0.70]%) AND the productivity percentage drop is ABOUT ([17.100]%) AND the reservoir pressure is ABOUT ([12.60] MPa) AND the oil production rate is ABOUT ([2,$max_{\text{Oil production rate}}$] t/day) AND the type of well is "Extractive" AND the reservoir injectivity is MEDIUM or GREAT, THEN it is possible to use the DISIN + HCl technology at the well.

Such rules are formulated by experts and put into the knowledge base of expert systems for their use in the fuzzy inference mechanisms in the process of solving practical problems [25].

The main disadvantages of the expert approach to the formation of a knowledge base in the decision-making support systems are:

1) high labor intensity (an expert needs to formulate, structure and formalize a set of rules);

2) low efficiency of practical use of the expert knowledge bases.

To eliminate them, this work implements an approach to the automatic formation of the knowledge base without an involvement of experts. Figure 1 shows a diagram of the proposed approach.

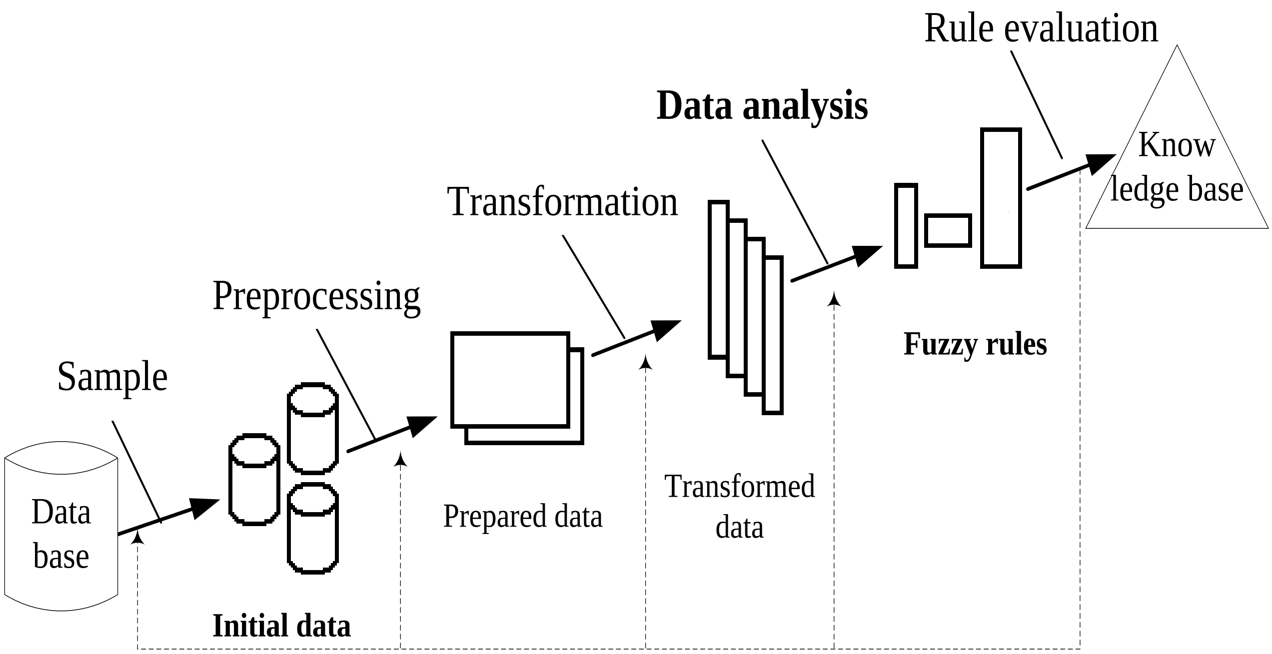

Fig 1. Data analysis and knowledge base formation scheme

As can be seen from the figure, the GTM selection in the oil fields requires the use of fuzzy production rules of the corresponding type. The paper proposes to use the following type of rules [18]:

$$\text{IF } x_1 = \overleftrightarrow{A}_1\ (w_1) \text{ AND } x_2 = \overleftrightarrow{A}_2\ (w_2) \text{ AND } \dots\ x_n = \overleftrightarrow{A}_n\ (w_n),$$
$$\text{THEN } y = B\ [CF], \quad (1)$$

where x_i – input variables, $w_i \in [0,1]$ – input weights, $\mu_{\tilde{A}_i}(x_i)$ – membership function, y – output variable, B – output value, $CF \in [0,1]$ – rule validity.

To create the rules of the form (1), it is proposed to use a specially developed neuro-fuzzy model. To build it, one need training and test data samples. At the same time, even the random nature of the samples does not guarantee high efficiency in the practical use of the knowledge base being formed. This approach is possible in case of data sampling, where the representativeness is beyond doubt. It is not always possible to obtain such initial data in real problems of neuro-fuzzy modeling and, in particular, in the oil industry. Therefore, it is advisable to train a fuzzy neural network iteratively several times, which is implemented in this study. For this purpose, we used the bootstrap method, which allows generating random data samples based on the method of random sampling with replacement [26].

As a result of applying this method, we built a set of fuzzy neural networks, which can be considered as a special neuro-fuzzy model of a parallel architecture (see Figure 2).

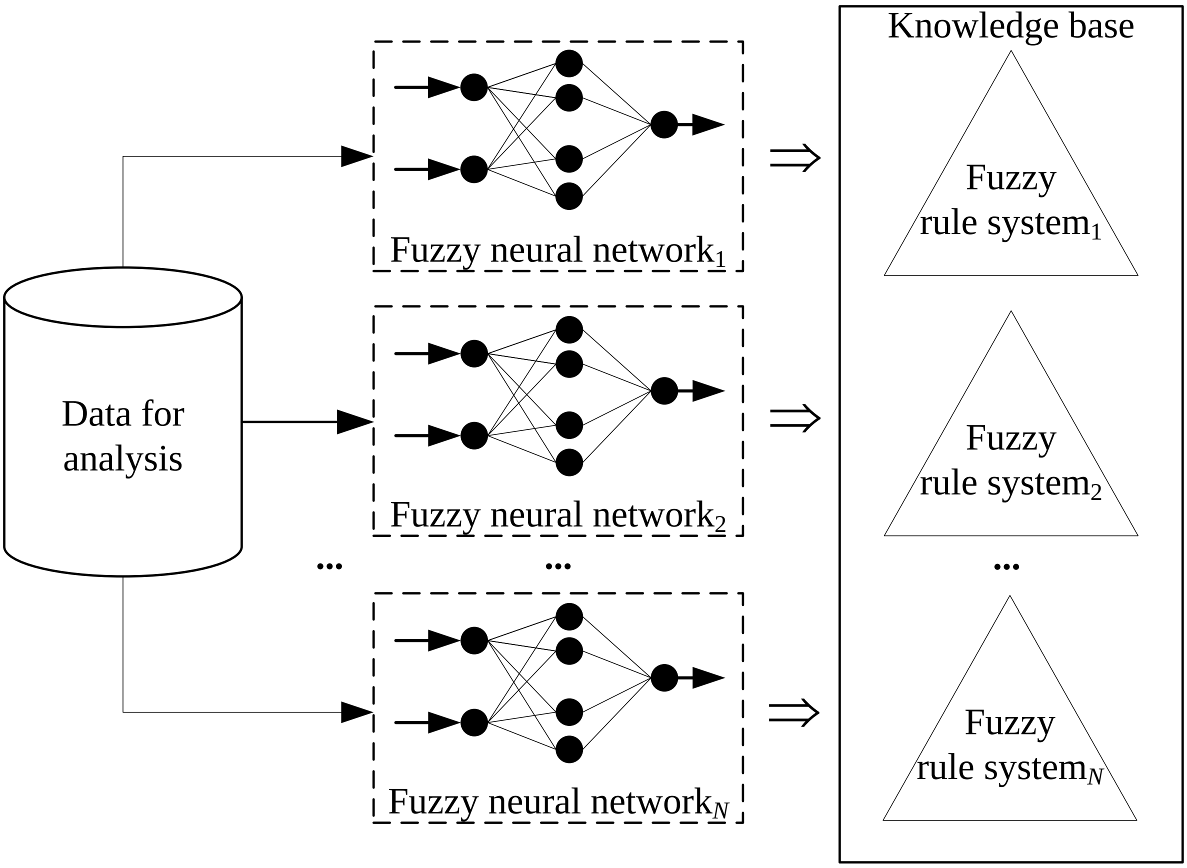

Figure 2. Scheme of forming a knowledge base based on a neuro-fuzzy model

In this scheme, training and testing of the corresponding fuzzy neural networks is performed on various random data samples.

To practically solve the GTM selection problem, it is necessary to set a problem and develop a scheme for the joint application of the knowledge base rules. In accordance with the task to be solved, the result of the GTM selection shall be considered the combination of intermediate results independently produced by each system of rules (see Figure 3).

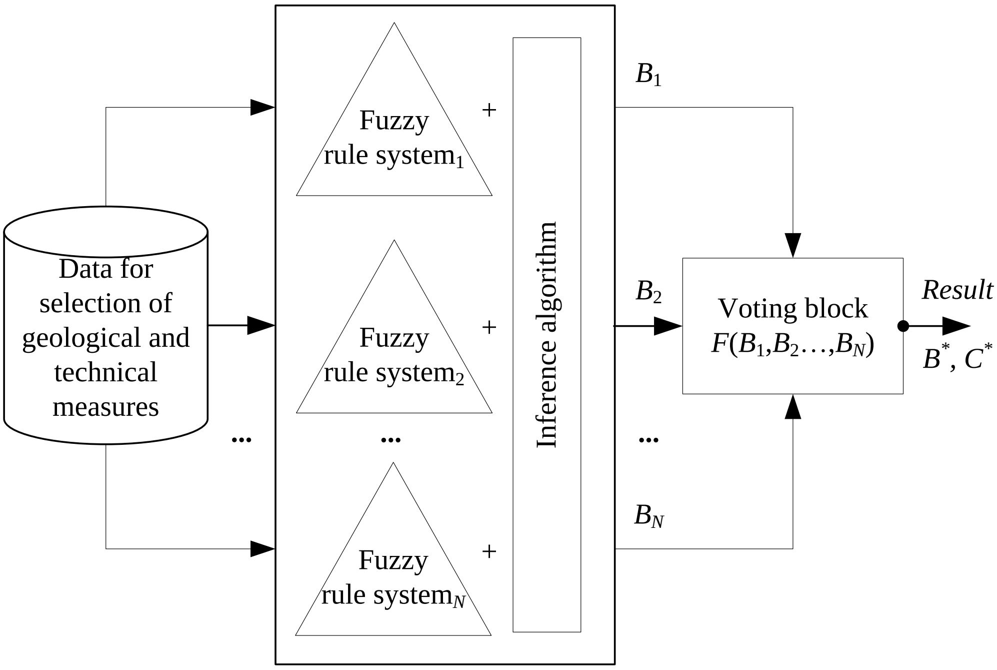

Figure 3. Scheme of joint use of knowledge base rules

The figure uses the following designations [27]: $F(B_1, B_2,\ldots, B_N)$ – voting rule, $B^* \in \{B_1, B_2,\ldots, B_N\}$ – required GTM, C^* – comprehensive assessment of the decision reliability. The result of the final assessment is a specific GTM B^*, as well as a comprehensive assessment of its reliability C^*.

The solution to this problem made it possible to build a neuro-fuzzy model and form a knowledge base for the GTM selection in oil fields.

III. RESULTS AND DISCUSSION

We tested the formed knowledge base on the example of solving the problem of GRM selection for various wells of the Feofanovskoye Field (Lukoil OJSC). The following input parameters were used in the initial data with a volume of 15,000 records, characterizing the specified field over the past 5 years:

- rock group;
- absolute rock permeability;
- rock porosity;
- initial oil saturation;
- initial oil-saturated thickness;
- sweep efficiency;
- current oil reserves;
- minimum flow rate of adjacent wells;
- average flow rate of adjacent wells;
- maximum flow rate of adjacent wells;
- minimum water cut of adjacent wells;
- average water cut of adjacent wells;
- maximum water cut of adjacent wells.

The following GTM were used as the output parameter values, which were recommended by experts for assignment in the oil fields in the past:

- oil bitumen product;
- high molecular weight compounds;
- injection;
- water-swelling polymer;
- cavern creation;
- deep hydrochloric acid effect;
- silicate-gel system;
- nepheline;
- modified silicate-gel system;
- organic silicon compound;
- colloidal-selective mixture.

The use of the generated knowledge base made it possible to select a list of GTM for wells, based on the conditions of their current operation (see Table 1).

Table 1. An Example of Geological and Technical Measures Recommended for Use in Production Wells

Geological and technical measures	The purpose of the geological and technical measures	Validity assessment,%
For well 687		
Oil bitumen product	Water limitation	82,6
High molecular weight compounds	Water limitation	82,6
Injection	Water limitation	78,9
Water-swellable polymer	Water limitation	78,9
For well 312		
Cavern creation	Stimulation	100
Deep hydrochloric acid effect	Stimulation	100
For well 314		
Cavern creation	Stimulation	100
Deep hydrochloric acid effect	Stimulation	100
For well 414		
Oil bitumen product	Water limitation	60,79
High molecular weight compounds	Water limitation	60,79
Injection	Water limitation	52,6
Water-swellable polymer	Water limitation	52,6
Silicate-gel system	Water limitation	44,07
Nepheline	Water limitation	44,07
Modified silicate-gel system	Water limitation	44,07
Silicon-organic compound	Water limitation	44,07
Colloid selective blend	Water limitation	44,07

The experiment results are satisfactory and are confirmed by the positive expert assessments, selecting geological and technical measures at this field.

IV. SUMMARY

In this work, we substantiated the expediency of the formation and practical use of fuzzy knowledge bases of the production type for the GTM selection. We considered the features of solving this problem and forming a knowledge base as the main component of the system being developed. We analyzed the traditional approach to the formation of a fuzzy knowledge base. We proposed an approach based on the stages of the knowledge detection technology in databases. For the GTM selection, we proposed a special type of fuzzy rules and a neuro-fuzzy model for their formation. The generated knowledge base was tested on the example of solving the problem of selecting geological and technical measures for various wells of the Feofanovskoye Field (Lukoil OJSC). The use of the knowledge base made it possible to select the optimal list of measures for the given wells. The experiment results are satisfactory and are confirmed by the positive expert assessments, selecting geological and technical measures at this field.

V. CONCLUSIONS

Thus, the problem of development and use of a neuro-fuzzy model for the formation of knowledge bases for the GTM selection was solved in the work. The results of our studies have shown the effectiveness of the proposed approach to solving the problem. The formed knowledge base showed high adequacy, consistent with the expert assessments. This indicates its efficiency and the possibility of practical use for the GTM selection.

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