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METHOD OF CREATION OF "CORE-GIS-SEISMIC ATTRIBUTES" DEPENDENCES WITH USE OF TRAINABLE NEURAL NETWORKS

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Abstract. The study describes methodological techniques and results of geophysical well logging and seismic data interpretation by means of trainable neural networks. Objects of research are wells and seismic materials of Talakan field. The article also presents forecast of construction and reservoir properties of Osa horizon. The paper gives an example of creation of geological (lithological -facial) model of the field based on developed methodical techniques of complex interpretation of geologic-geophysical data by trainable neural network. The constructed lithological -facial model allows specifying a geological structure of the field. The developed methodical techniques and the trained neural networks may be applied to adjacent sites for research of carbonate horizons.

1 Introduction

Dependence establishment between a complex of geophysical investigations (GIS) in a prospecting well and the actual material in rock samples form (core) is complex and relevant objective of geological exploration. Coring along wellbore in a production range covers only a small part of well, in relation to intact samples extraction difficulties and, as a rule, a small sinking with coring opened by well in production range of the geological section.

The standard technique of GIS data interpretation allows to calculate total porosity factor (f_p) of breed's and component structure of a collector along wellbore. Calculations were implemented by means of linear petrophysical equations system solution, according to the established model of solid matrix. For the studied field (Talakan oil-gas condensate field) the model of solid matrix consists of dolomite, clay, salt, chalk-stone and anhydrite.

The combined equation was solved by using a system of methods: neutron gamma logging (NGL), gamma-ray density logging (GDL), acoustic logging (AL). Other methods of the GIS are auxiliary at standard technique application for identification of porosity factor and component structure of collector.

Auxiliary complex of the Talakan field consists of such GIS methods as density logging (DL), micro lateral resistivity logging (MRL), well diameter logging (WDL).

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In general, the technique based on lithological model of solid matrix creation by a system of NGL,GDL, AL GIS methods, significantly underreports porosity factor (f_p) in a carbonate collector because caverns are neglected in spite of the type of producing Osa horizon collector, which is characterized as complex cavern porous-fissured collector.

Unlike the standard technique, the benefit of mathematical tool of neural networks is possibility of all input data usage, in our case, GIS data (including the methods, for which linear dependences between values of logging and collector properties are absent and have difficult interpreted nonlinear nature). Compared to a standard technique, use of all GIS data allows carrying out the forecast of the physical parameters, characterizing collector along well trunk. As a result, it raises the essentially greater number of data to describe a geological section in well [1–3].

This paper offers the technique of geological field model creation based on establishment of standard joints between analytical researches of core material, GIS data and dynamic attributes of the seismic wave field by means of neural networks (core – GIS – seismic attributes).

Combination of geological -geophysical data was carried out by mathematical tool of neural networks implemented by means of "NeuroInformGeo" intellectual geographic information system, developed in "InformGeoService" LLC (O. M. Gafurov). "InformGeoService" LLC in concern with "Krasnoyarskgeophysics" CJSC (A.A. Kontorovich, D. O. Gafurov, etc.) created forecasting methods development of geological section and evaluation of Osa horizon collectors (Talakan field).

During the period from 2004 to 2015, the technique has gained further development in relation to various petroleum districts based on "InformGeoService' LLC ' (O. M. Gafurov) and "RN-Krasnoyarskpetroleum R&D Institute" LLC (A.K. Bitner, A. A. Kontorovich, D.O.Gafurov). In 2011, certificates and the Russian Federation patent were received [4].

2 Core material analysis

Analytical researches of core material and assessment of Osa horizon breeds reservoir properties have been performed by analyzing the well materials data. Wells are located in different parts of the field. Talakan field core material was selected in rather small amounts; less than 10% of wells with a representative core recovery (>70%) were drilled in the range of the productive Osa horizon.

After conducting analytical core material researches, as a result, we allocated nine lithological types of the breeds, which are characterized by various reservoir properties (Table 1). According to analytical researches results, wells test results, hydrodynamic logging (HDL), etc., boundary values for carbonate collectors have been determined. For Osa horizon carbonate collectors of the Talakan field: porosity factor f_p >6%, clayiness index I_{cl} <10%.

Table 1. Reservoir properties of lithological types of the Osa horizon breeds.

Lithology	Reservoir characteristics, %	Comments
Salt;	$K_p < 1$	Not collector
Clay material;	$K_p < 2$, $K_{sh} > 25$	Not collector
Salinized dolomites, calcareous, sulphated, clayed;	$K_p < 1$, $K_{sh} = 10- 12$	Not collector
Clay dolomit, chalk-stone dolomits;	$K_p = 2…6$, $K_{sh} < 10$	Not collector
Anhydrite – lowclayed dolomit;	$K_p < 2$, $K_{sh} < 10$	Not collector
Lowclayed - bituminous sulphated dolomit;	$K_p = 6…10$	Collector

Organogenic porous dolomit with trace impurity of terrigenous materials, sulphates and salts	$K_p = 10…15$	Collector
Organogenic highly porous dolomit.	$K_p \geq 15$	Collector

The analysis shows that reservoir properties of the allocated lithological types are rather well sustained on the area. Well-logging curves and the allocated lithotypes allow carrying out the forecast of collecting properties of breeds along wells trunk, which did not provide with core material.

3 Establishment of core-GIS dependence, forecasting of lithological types of breeds along well trunk

The review of domestic and foreign [5–10] studies devoted to interpretation of the geological – geophysical data by neural networks, indicates researchers tendency to focus attention on the choice of an optimum mathematical training method of neural network, at preservation of the simplified triplex architecture. The present work offers quite different approach. The main idea is creation of training boundary conditions (criteria) under which the dynamic mechanism of a neural network architecture adaptation goes to sophistication and increasing the quantity of training examples. Figure 1 presents the scheme of neural networks application implemented in the present work.

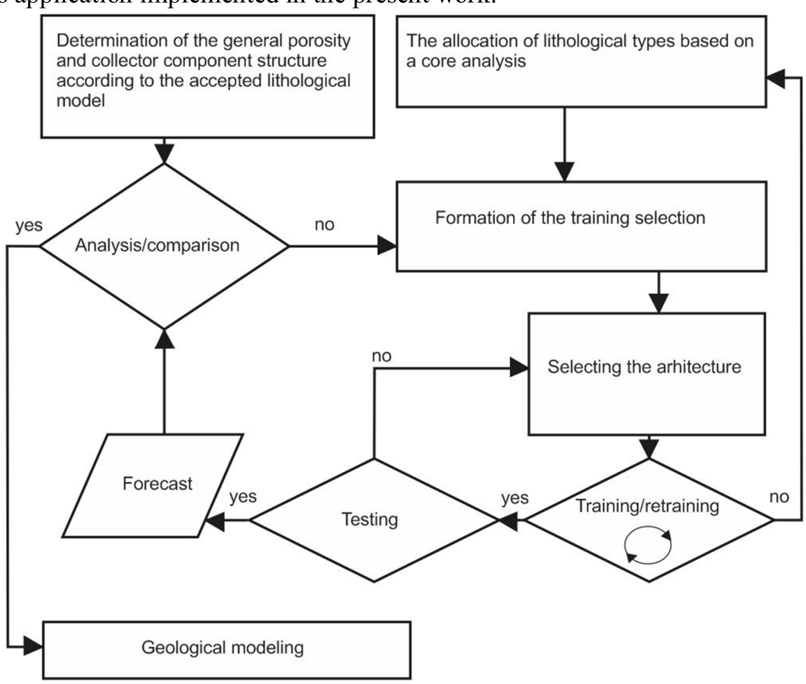

Figure 1. Scheme of the method of GIS data interpretation by trainable neural networks.

The full range of GIS used in neural network configuration includes the following system of methods: GL, NGL, WDL, AL, DL, MRL, and GDL. Additional studies consisted of hydrodynamic logging (HDL) and formation testing of log cable (TLC).

Forecast technique of lithological breeds types and effective thickness of the Osa horizon by GIS, which is set on intervals of lithological breeds types on a core, includes the following set of procedures [11–12]:

- selection of initial elementary architecture of a neural network;
- forming of the training selection, representing comparison of lithological breeds types intervals (classes) to discrete counting of the readings taken from GIS diagrams;
- choice of the boundary value, determining forecast quality in %;
- training of a neural network (Fletcher-Reeves conjugate gradient method) and forecasting;
- check of forecast results on the reference data which have entered to training selection;
- check of forecast results on the examination data, which are not included in the training selection.

Successful result means that the task is solved, negative result means that system gives a value of the maximum forecast probability and sophistication of network architecture happens automatically. In other words, the quantity of layers and neurons increases and calculation of expected parameters repeats. This process is non-infinite. After a number of iterations, network architecture sophistication process stops and the best result, received in the previous iterations, is considered as the optimal solution.

Figure 2 presents three examination wells (wells provided with the full GIS complex and representative core recovery). Examination wells have not entered to the training selection, where the neural network shows allocation and forecasting results.

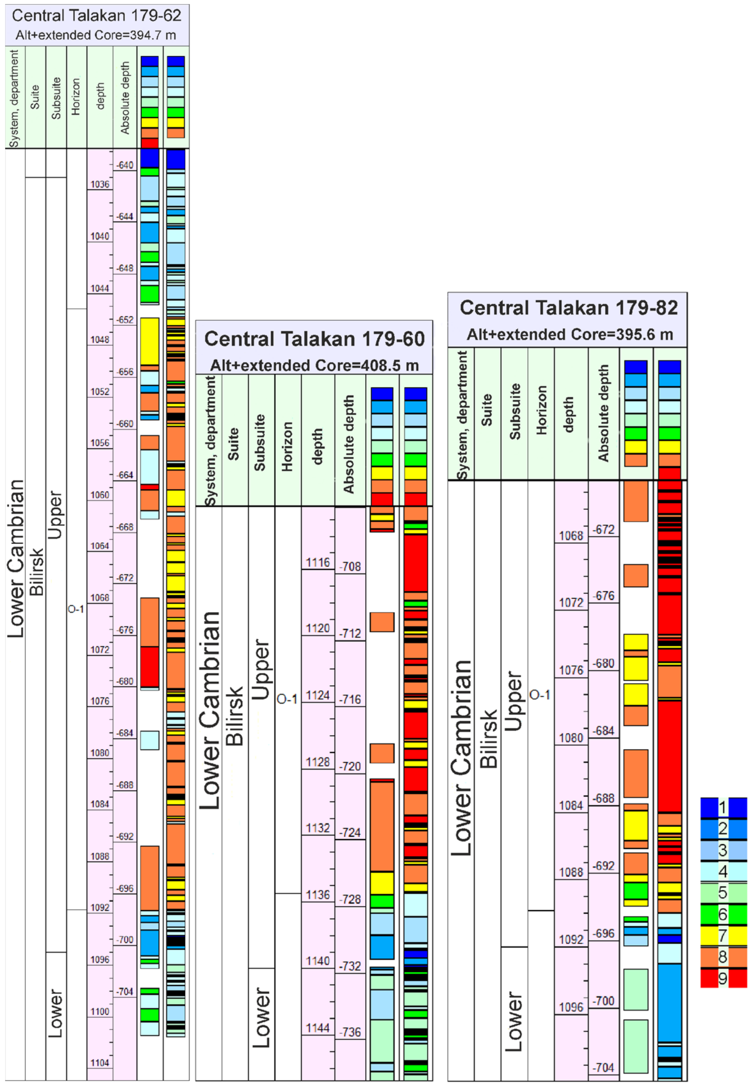

Figure 2. The tested wells (in the left column contains the allocated lithotypes on a core, in the right – expected values of lithological types along well trunk). A color scale of compliance to nine allocated classes of lithological breeds types. ***Not collector:*** 1*) salts 2) clay material;3) salinized dolomites, calcareous, sulphated, clayed; 4) clay dolomit, chalk-stone dolomits; 5) anhydrite dolomit calcareous (nonporous) highly clayed; 6) anhydrite – lowclayed dolomit.* ***Collector:*** *7) lowclayed - bituminous sulphated dolomit; 8) Organogenic porous dolomit with trace impurity of terrigenous materials, sulphates and salts; 9) Organogenic dolomit highly porous porosity factor.*

Figure 3 gives comparison of application results between standard technique of GIS interpretation and neural networks application with the most characterized core information to an examination well. There are dependences on the productive Osa horizon for 160 discrete reports of examination well. Dependences given in Figure 3 testify to higher quality of the forecast mathematical tool of neural networks.

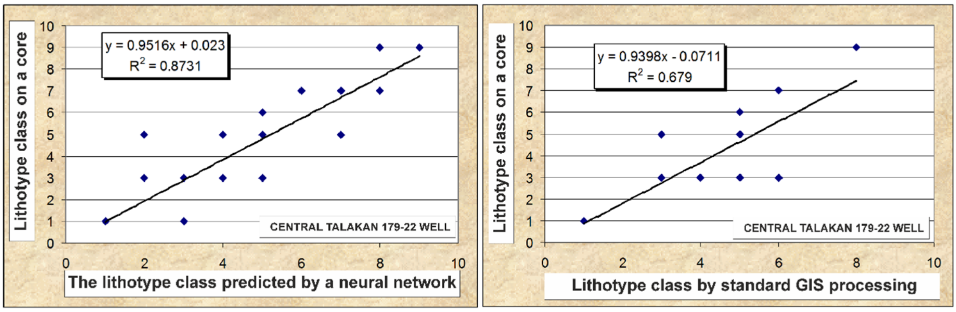

Figure 3. Comparison of GIS data interpretation techniques.

4 Establishment of GIS –seismic wave field attributes dependence, forecasting of effective thickness of the productive horizon

Seismic material during adaptation of technique presented by 2D irregular network of the seismic profiles, fulfilled on the Talakan field. Based on results of complex interpretation of analytical data, GIS materials and seismicity it was supposed to perform map development of the effective flooding space thickness of the Osa horizon with further creation of facial zonation scheme. The purpose is profound understanding of field geology and distribution of layer physical properties on the area.

Technique implementation in "NeuroInformGeo" geographic information system looks as follows:

1. Networks of N_a dynamic areal attributes with common starting point are coming to input.
2. In order to form etalon, wells N_s are used, in which tests the GIS have been carried out. For areal interpretation, all wells are getting to given or preselected area, and being in close proximity to a profile or in a band of confidential probability from a profile. Wells break into classes of the predicted geological sign.
3. For every i^{th} well, where i=1,…, N_s , based on geophysical attributes, $D_i\{x,y\}$ variety of a set of n_i points lying in a radius R_i with the center in i^{th} well. The choice of a confidential interval radius depends on geological conditions and well environment parameters. Whereby, all points, which have got to confidential space near one well carry identical information capacity.
4. The standard formation in the vector form with the average values of geophysical parameters and scales, which provides informative contribution assessment of each parameter. Points in a circle used for registration of an image or classes. Formation of vectors with coordinates $\{x,y\} \in D_i$ and geophysical parameters values implemented by using a set of the calculated coordinates near the wells $D_i\{x,y\}$. At the same time, for each j^{th} point from the $D_i\{x,y\}$ variety , vector V_j^i (with length of N_a +1) is formed. The components of vector are values of v_{j1},…, v_{jN_a} geophysical parameters attributes and class number k , to which i^{th} well is related: V_j^i = (v_{j1},…, v_{jN_a} ,k). Thus, sample constructed on the set of points

$D_i\{x,y\}$, relating to i^{th} well, is the set of vectors $U_j^i=\{V_1^i, V_2^i,\ldots,V_{n_i}^i\}$. Sample constructed on all chosen wells is formed by the set:

$$U=\bigcup_{i=1}^{N_s} U_i = \{U_1,\ldots,U_{N_s}\} \tag{1}$$

5. Wells, which are in a strip of probability belief in the first iteration, are dividing into two parts. One part of wells are used as etalon sample, another part forms test sample in a random way for forecast quality testing. In other words, the set of U is divided into two subsets U_{train} and U_{test}, forming training and test samples.
6. Multilayered neural network with N_a input and one output neuron, accepting OUT $\in$ value to the allocated k class value is forming by a method of neural networks training technique based on back propagation of error algorithm. Neural network is training on a set U_{train}. We select the architecture of a network empirically, and it provides the minimal training error.
7. Importance indicators χ_{N_a} are defined for each N_a of input parameters. This type of indicators characterizes informative contribution of known parameter (attribute) to results. The neural network calculates a gradient of assessment function on input signals and the trained values of a network. Thus, following formula determines the importance indicator N_a of the parameter in solving *q-o* case:

$$\chi_{N_a}^q = \left| \frac{\partial H_q}{\partial w_{N_a}} (w_{N_a} - w_{N_a}^*) \right| \tag{2}$$

where, in *q*-o case solving, importance indicator shows how much *q*-o case solving assessment function value can be affected. If running value of w_{N_a} parameter changes to next designated value $w_{N_a}^*$ for N_a parameter. Final parameter of signification N_a is calculated as general mean:

$$\chi_{N_a} = \frac{1}{n}\sum_{q=1}^{n} \chi_{N_a}^q , \tag{3}$$

where n is number of cases. Thus, calculated value of signification parameter for N_a parameter assumes, in linear fit, absolute value of assessment function variation at input parameter (signal) moving off from the network. Non-informative parameters are moving off from the network and neural network is retraining.

8. Training control handled by comparison of predicted values variety with a set of assigned classes value in testing wells U_{test}. In the set of value U_{test} network generalization error is calculated by divergence network answers with known answers. If results are not satisfactory, training repeats. By cross validation technique the set U is divided again into two subsets U_{train} и U_{test}, which forming training and testing selections in the ratio *4/5* and *1/5*. Training and testing are implemented by forecast correlation factor calculation with testing sample. Farther, by all possible methods we divide initial sample multistage with saving of forecasting classes intervals and with network architecture sophistication. In result of iterations, true average error of neural networks extension is calculated. In case

of unsatisfactory results, next decisions have to be implemented: rechecking of initial geological geophysical data, another value forecasting possibility, which also characterize investigated environment.

9. In case of satisfactory problem solving, forecast is start. The program divides all multidimensional attribute space into classes of fixture or similarity to one or other standard and in output forms the map of standards for areal interpretation or forms a section with allocation of complexes (classes) to temporary or deep model.

As a result of training and testing, the set of seismic parameters has been determined. This set has allowed to perform with rather high degree of reliability effective thickness and facial situations forecast in Osa reservoir forming on Talakan area. As an example, Figure 4 gives effective thickness map of Osa horizon in Talakan field.

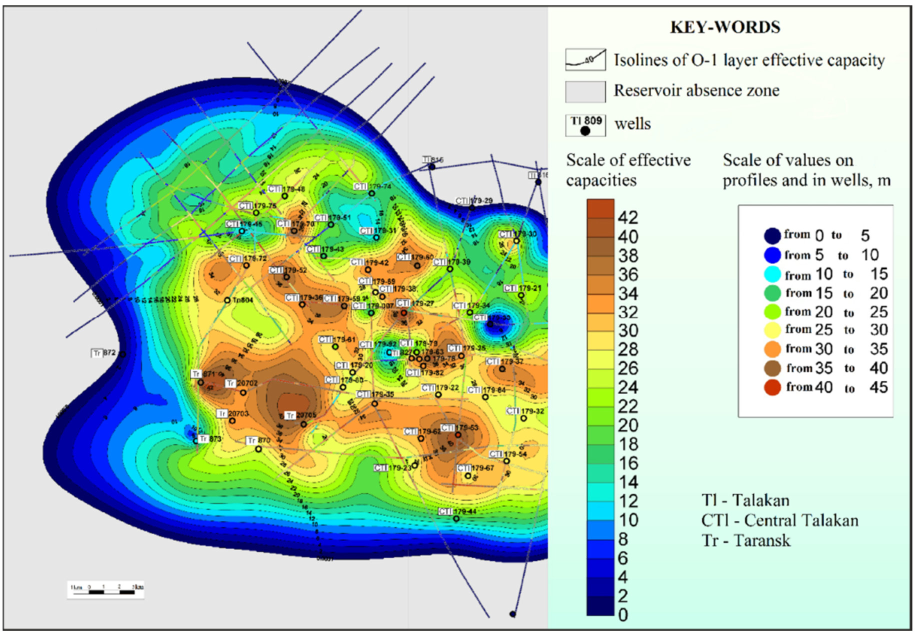

Figure 4. Forecasting map of effective thickness of Osa horizon collector.

5 Lithological facial field model creation

We constructed the lithological facial scheme of the Talakan field within checking results of coherence forecast to geological ideas about object. Scheme construction based on detail lithology splitting of subsuite drift by «NeuroInformGeo» geological information system, by forecasting of effective thickness and core analysis results. Figure 5 presents selected facial conditions of sedimentation in lithology facial scheme. Distribution of conditions on the field area (laterals) and in a vertical sense of upper Berilsk subsuite also has shown in scheme.

Complex analysis of geological –geophysical material shows that, collector properties of Osa horizon in Talakan field depends on paleogeography of sedimentation area:

- the best collectors zones of Osa horizon connected with organogenic dolomites, which formed in central and peripherical parts of organogenic structure;
- mostly, organogenic saline dolomits characterized by transient effective thicknesses. Their formation carried out in lagoon conditions with low water exchange.

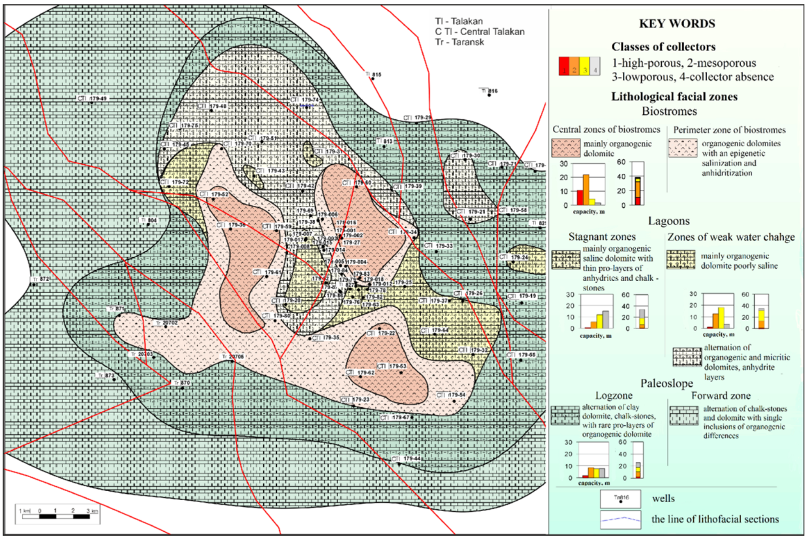

Figure 5. Lithological – facial scheme of oil, gas and condensed steam field.

6 Conclusion

One of the most important and complex tasks, which faces geologists and geophysicists carrying out researches on the Siberian platform, is reduced to collectors quality forecast of the carbonate Vendian and the Cambrian horizons, in which amount of oil and gas are concentrated. The problem of small volume of core selecting is particularly acute at GIS materials analysis stage for the purpose of lithological-petrophysical wellcuts creation and at the forecast of areal distribution of a collector, which can be carried out only according to subaerial geophysical measurements.

Standard recovery of lithological-petrophysical wellcuts determines success of the testing intervals by GIS materials choosing. It means that the reliable forecast of collectors distribution on the area can form a reliable basis for the planned wells location and diggings solid model creation.

The executed researches shows that neural networks application in case of analytical data integration, GIS materials and seismic exploration allows solving the following tasks: problems of geological section forecasting and collectors quality evaluation of both by wells, and on the area. Developed methodical techniques with some calibration can be used at the stages of investigation and additional exploration of oil and gas fields in the carbonate horizons of already found fields. In addition, taking into account statistical data at a search, these techniques can be used at the territories, which are poorly studied by drilling [12].

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