

UDC 553.04

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## ESTIMATION OF RESIDUAL WATER SATURATION IN 3D GEOLOGICAL MODELING

### Introduction

At the present time, a framework of the majority of studies connected with prospecting, exploration and extraction of hydrocarbons is digital modeling [1, 2]. In this connection, emphasis is laid on evaluation of change in residual water saturation. This is important, in the first place, for the evaluation of the oil saturation index (gas saturation index). Accuracy of the evaluation governs correctness of appraisal of hydrocarbon reserves, development of hydrocarbon production projects [3, 4], as well as detection of reservoir rocks to be stimulated [5]. Currently, the dominant method of oil and gas saturation modeling is interpolation of borehole data with regard to location of contacts between fluids. In the meanwhile, the influence exerted by the reservoir properties on the residual water saturation and, accordingly, on the value of the oil saturation index, is neglected. The proposed calculation approach to residual water saturation is expected to enhance efficiency of engineering research on extraction of difficult hydrocarbon reserves [6–8]. The chief difference from all previous techniques is the fact that instead of one value of residual water saturation, a histogram of this parameter is calculated for each cell.

### Goal of implemented research

The newly developed methodology is targeted at enhanced reliability evaluation of the oil saturation index of a reservoir based on the analysis of change in residual water saturation which exists in a sufficiently stable probabilistic relation with the reservoir properties, which allows calculation of an oil saturation cube almost in all available programs meant for complete three-dimensional geological modeling. In particular, for an all-oil zone, the unknown coefficient is less than porosity by a volume occupied by water which is impossible to remove using conventional methods. Nearby a water–oil contact, it is also necessary to take into account the action of capillary forces. They are connected with the permeability of pay zones [9] which are expedient to be modeled using probabilistic techniques [4].

### Valuation of maximum possible volume of voids filled with hydrocarbons

The method of evaluation of residual water saturation uses the lab-scale testing data on petrophysical properties of rocks [10]. The quality of such tests governs the accuracy of the unknown quantity in many ways. On the whole, there is a traceable general trend of decreasing residual saturation with increasing reservoir properties of test samples. Nonetheless, the scatter of the resultant values is rather wide, which points at the probabilistic type of relations between the study parameters (Fig. 1). Actually, using the obtained empirical formulas which approximate relations of the study parameters, it is difficult to predict the value of the target index even in

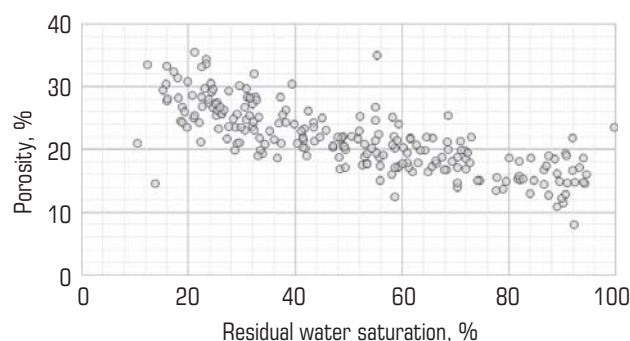
*This article discusses a new method of determining distributional patterns of residual water saturation in reservoirs during digital geological modeling. This is important for the construction of an oil saturation cube and prediction of character of stimulation of a hydrocarbon-bearing formation. Currently, construction of oil saturation cubes uses interpolation of borehole data. The reservoir properties of formations, which have influence on the nature of rock saturation, are neglected in this case. Considering essential scatter in the values of the study parameter and the comparatively large dimensions of the model cells, it is suggested to calculate histograms of residual water saturation coefficients. First, from the core testing data, the probability of non-exceedance of a certain critical water saturation value (80, 60, 40, 20) is calculated as function of porosity. For adapting the resultant dependences to larger objects, the unit cells are represented as sets of virtual rocks, with the sizes comparable with the sizes of core samples; the random number generator gives these rocks the values of reservoir properties such that the initial average values of porosity of the cells are preserved. For each type of conventional rock, the probability of non-exceedance of critical residual water saturation is calculated and the average values of the parameter are determined per cells. The relations between the probability of non-exceedance of critical water saturation and the porosity are approximated. Then, percentages of rocks within certain ranges of residual water saturation in a cell are determined. For the cube construction, the oil saturation index in an all-oil zone will be equal to the difference between one and residual water saturation, and will also depend on the height of rock occurrence above the water–oil contact in a water-and-oil zone.*

**Keywords:** reservoir, residual water saturation, porosity, reservoir properties, oil saturation index, core, rock, geological model

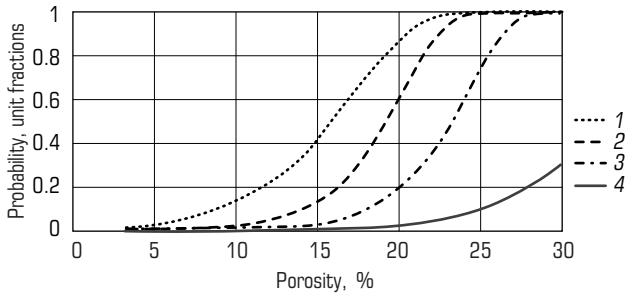
**DOI:** 10.17580/em.2024.01.06

individual samples as a significant error is possible. Even more difficulties appear in studying larger objects since transition to a higher scale involves by-effects, as a rule [11]. For example, the size of a cell of a geological model is larger than a sample by 10 million times. In this case, it is probable that there is a sufficient volume of rocks with drastically different residual water saturation as against the calculated value. This can be governed by the expansion of deposits with different porosity and by the structural nonuniformity of the void space [12–14].

It is expedient to model residual water saturation of rocks using probabilistic methods [12, 15–18]. To this end, the test samples are divided into 5 sets with respect to the study parameter. The first set is rocks with the residual water saturation ranging between 0 and 20%, the second set — 20–40%, the third set — 40–60%, the fourth set — 60–80% and the

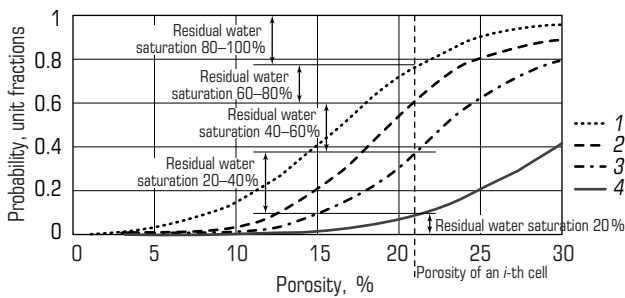


**Fig. 1.** Example of the residual water saturation–porosity relationship for the Upper Jurassic terrigenous deposits in the west of the Ural trough



**Fig. 2. Relationship between the probability of non-exceedance of critical water-retaining capacity and the porosity of the Upper Jurassic terrigenous deposits in the west of the Ural trough:**

1 – residual water saturation not higher than 80%; 2 – residual water saturation not higher than 60%; 3 – residual water saturation not higher than 40%; 4 – residual water saturation not higher than 20%



**Fig. 3. Illustrative relationship between the probability of non-exceedance of critical water saturation and the porosity on the scale of a cell in the geological model of the Upper Jurassic deposit of the Cis-Ural trough:**

1 – residual water saturation not higher than 80%; 2 – residual water saturation not higher than 60%; 3 – residual water saturation not higher than 40%; 4 – residual water saturation not higher than 20%

fifth set — 80–100%. For each set, the relationships of porosity and probability of non-exceedance of the critical residual water saturation (80%, 60%, 40%, 20%) are obtained. The results are approximated by empirical formula (1) (Fig. 2). The coefficient of correlation of these functions ranges as 0.90–0.98.

$$P_{ws}^{cr} = 1 - \exp\left[-\exp\left(AK_{por}^c - B\right)\right], \quad (1)$$

where  $P_{ws}^{cr}$  is the probability of non-exceedance of the critical residual water saturation, unit fractions;  $K_n^c$  is the porosity determined from core testing, unit fractions;  $A, B$  are the coefficients of proportionality.

The empirical formulas (see Fig. 2) have a pronounced asymptotics in the domains of low and high porosities. For the compact samples, it is typical that probability of certain conditions to be true is minimal, while for the porous samples, vice versa, the function strives to one, which conforms with the logic of the phenomenon. At the same time, with the lower threshold of residual water saturation, it becomes more difficult to find samples which meet the requirements. This situation seems to be quite regular, and it is proved by the analysis of properties of most sets of rock samples with dominating pore type of voids.

For switching to the analysis of larger objects than rock samples, it is required to adapt the dependences obtained on a lab scale. A simple calculation of probabilistic characteristics using formula (1) in geological modeling hardly can be assumed as correct. In this respect, it is required to introduce corrections to account for the change in the scale of the analysis [4]. In this case, it is advisable to use a Monte Carlo method [17, 18]. First, it is imagined that a cell of a geological model consists of many virtual rocks having sizes which are close to the sizes of samples meant for the lab-scale studies. Then, all conventional rocks are attributed reservoir properties by

a random number generator. This operation involves some constraints to be obeyed, namely [12]:

1. The average values of porosity of all virtual collections conforms with the primary reservoir properties of each cell in the digital geological model;
2. The log-normal distribution of porosity is assumed for samplings of conventional rocks;
3. The mean square deviation of a virtual collection porosity is never higher than a half average value of the matching cell in the geological model.

Then, for the virtual rock collections, using formula (1), the probabilities of non-exceedance of critical residual water saturation are calculated. After that, for each conventional collection, a mean geometric value is calculated and the unknown parameter–porosity relation is approximated (formula (2), Fig. 3). The coefficient of correlation between the initial and calculated values ranges as 0.97–0.99.

$$P_{ws}^p = 1 - \exp\left[-\exp\left(A_1K_{por}^2 + B_1K_{por} + C\right)\right], \quad (2)$$

where  $P_{ws}^p$  is the probability of non-exceedance of critical water saturation per cell, unit fractions;  $K_{por}$  is the cell porosity, unit fractions;  $A_1, B_1, C$  are the coefficients of proportionality.

These functions describing the probability of non-exceedance of critical residual water saturation make it possible to calculate the histogram of this parameter for each cell. For calculating the probability of hitting the wanted range of rocks with the required residual water saturation, it is necessary to find a difference between the corresponding functions of distributions. In this manner, we obtain a framework for the automated calculation of a residual water saturation histogram for each cell in the whole geological model simultaneously. Implementation of this operation is possible in any software meant for 3D geological modeling.

Residual water saturation modeling enables a more comprehensive evaluation of change in the oil and gas saturation index. First of all, this relates to the zones in a hydrocarbon field, which contain no water-bearing reservoirs, i.e. all-oil zones. In this case, the sum of the residual water saturation coefficient and the oil and gas index is equal to one. In this way, based on modernization of the appropriate graphs of residual water saturation in a digital form, it becomes possible to create histograms of the oil saturation index for all cells of a geological model. As a result, we observe a logical pattern in the change of the test parameter as function of porosity. As the reservoir properties of rocks improve, there is a positive trend of increasing oil saturation index (Fig. 4). The probabilistic nature of the study parameter dependence on the average porosity of geological cells is fairly observable. Furthermore, for the comparison, Fig. 4 gives also the calculated values of the study parameter. On the whole, there is no profound disagreement between the cited data. On the other hand, the proposed approach gives information on the scatter existing between values, which improves calculation reliability in hydrodynamic models.

Some complexities appear when determining oil and gas saturation index for cells nearby the oil and water interface. In this case, it is necessary to take into account the capillary forces which are in a sufficiently tight connection with the permeability of rocks. As a rule, their increasing effect on water saturation decreases as the poroperm properties of rock in pay zones improve [9]. It is possible to predict nonuniform permeability in the cells of the models using the probabilistic methods [12].

**Conclusion**

Construction of a residual water saturation cube can enhance reliability of productive strata saturation estimate both qualitatively and quantitatively, toward the benefit of appraisal accuracy of oil and gas reserves.

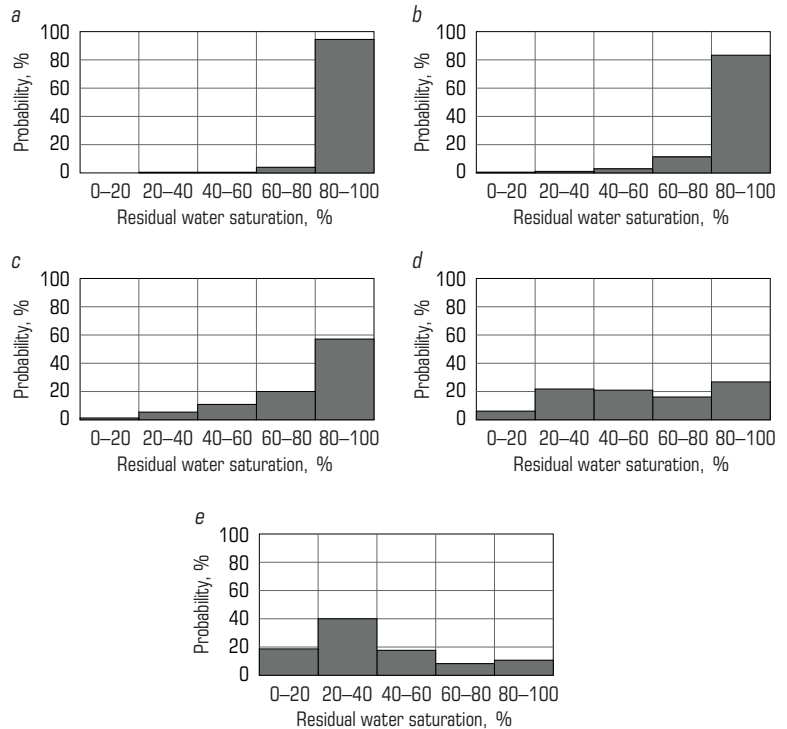
This approach to estimating nonuniformity of an oil / gas saturation index expressed in terms of the residual water saturation can help minimize negative phenomena [3, 15, 19, 20] during stimulation of hydrocarbon-bearing formations, and identify zones which can be insensitive to the stimulation. Calculation of probable characteristics of saturation and

the scatter of these values per all cells is expedient to use in assessment of geological risks of oil and gas field development.

Substitution of information on oil and gas saturation from borehole data interpolation without regard to the nonuniformity of petrophysical properties of rocks for the data on quantification of scatter in the target parameters can lead to the necessity of revision of hydrodynamic modeling methodology and, consequently, design methods of hydrocarbon extraction. Furthermore, the proposed approach to assessing properties of productive strata creates a background for boosting the use of information technologies in oil and gas field development.

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**Fig. 4. Model comparison of calculated values and histograms of residual water saturation for geological model cells with different average porosities:**

a – calculated residual water saturation – 100%, average porosity of cell – 5%; b – calculated residual water saturation – 90.4%, average porosity of cell – 10%; c – calculated residual water saturation – 73.4%, average porosity of cell – 15%; d – calculated residual water saturation – 56.4%, average porosity of cell – 20%; e – calculated residual water saturation – 39.3%, average porosity of cell – 25%

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