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Statistical Justification for the Formation of Skin Factor Values during Acid Treatment in Layered-Heterogeneous Bashkir Deposits of Perm Krai

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Статистическое обоснование формирования значений скин-фактора при проведении кислотных обработок в слоисто-неоднородных башкирских отложениях Пермского края

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Carbonate deposits of the Bashkirian Stage in Perm Krai are characterized by a high degree of heterogeneity, which makes it difficult to develop oil reserves evenly. Acid treatments are currently one of the most popular methods of regulating development in carbonate reservoirs. However, in conditions of layeredheterogeneous sediments the most permeable part of the section is mainly affected, while the low-permeable part of the section remains uninvolved in the development process. In this connection, it is an urgent task to predict the degree of impact of acid treatment on individual reservoir layers. The purpose of this study was to create mathematical models for predicting the skin factor of the reservoir after acid treatment. As input data we used skin factor determinations in reservoirs and geologic characteristics of these reservoirs: porosity coefficient, permeability coefficient, oil saturation coefficient and reservoir thickness. Mathematical modeling methods were used in the study: stepwise regression analysis, construction of probabilistic-statistical models. According to the results of statistical analysis it was revealed that reservoirs are divided into two classes, in which the formation of the skin factor value depends on different characteristics of the reservoir. To determine the class to which the reservoir formation belongs, univariate probabilistic-statistical models were built and subsequently combined into a single complex model. For each identified class, regression models were developed to predict the skin factor of the formation after acid treatment. The obtained mathematical models can be applied in the design of geological and technological measures, as well as to improve the accuracy of hydrodynamic modeling by taking into account the values of skin factors in the bottomhole zone in the adaptation of the model.

Ключевые слова:
пошаговый регрессионный анализ, вероятностно-статистическая модель, комплексная вероятность, кислотная обработка, карбонатный коллектор, скин-фактор, пористость, проницаемость, нефтенасыщенность.

Карбонатные отложения башкирского яруса в Пермском крае характеризуются высокой степенью неоднородности, что затрудняет равномерную выработку запасов нефти. На сегодняшний день одним из самых популярных методов регулирования разработки в карбонатных коллекторах является проведение кислотных обработок. Однако в условиях слоисто-неоднородных отложений воздействию подвергается преимущественно наиболее проницаемая часть разреза, а низкопроницаемая часть разреза, напротив, остается не вовлеченной в процесс разработки. В связи с этим актуальной задачей является прогнозирование степени воздействия кислотной обработки на отдельные пропластки коллекторов. Целью настоящего исследования являлось создание математических моделей для прогнозирования значений скин-фактора пропластка после проведения кислотной обработки. В качестве исходных данных были использованы определения скин-фактора в пропластках и геологические характеристики этих пропластков: коэффициент пористости, коэффициент проницаемости, коэффициент нефтенасыщенности и толщина пропластка. В исследовании использовались методы математического моделирования: пошаговый регрессионный анализ, построение вероятностно-статистических моделей. По результатам статистического анализа выявлено, что пропластки коллекторов разделяются на два класса, в которых формирование значения скин-фактора зависит от различных характеристик пропластка. Для определения класса, к которому относится пропласток построены, одномерные вероятностно-статистические модели, которые впоследствии объединены в единую комплексную модель. Для каждого выделенного класса разработаны регрессионные модели для прогноза скин-фактора пропластка после проведения кислотной обработки. Полученные математические модели могут быть применены при проектировании геолого-технологических мероприятий, а также для повышения точности гидродинамического моделирования путем учета значений скин-факторов по пропласткам в призабойной зоне при адаптации модели.

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Introduction

The Bashkir deposits in the Perm region are characterized by layered and lateral heterogeneity due to which the development of oil reserves is uneven [1–4]. In order to regulate development and ensure full development of reserves, various methods of enhancing oil recovery and intensifying oil production are used. One of the most common methods for carbonate reservoirs is acid treatment. However, in conditions of layered heterogeneous deposits, the most permeable part of the section is predominantly affected and the low-permeability part remains uninvolved in development [5–9]. To assess the degree of acid treatment impact on individual interlayers, the skin factor being a complex indicator characterizing the state of the bottomhole formation zone is used. In this paper a method for predicting the skin factor of individual interlayers is proposed based on a number of their characteristics.

Studying the influence of interlayer characteristics on the skin factor formation

The initial data for the study were the definitions of the interlayer skin factors in conjunction with the interlayer characteristics: porosity coefficient K_p, permeability coefficient K_{pr}, oil saturation coefficient K_o, interlayer thickness N_{il}.

For comprehensive studying the formation of skin factor S values from the geological characteristics of interlayers, a set of multidimensional step-by-step regression equations was built. The formation of this complex occurred according to the following algorithm:

1. All observations are ranked by the value of the skin factor S from minimum to maximum.

2. The first regression model is built on the basis of the first three observations characterized by the lowest skin factor values.

3. While building subsequent regression models, the number of observations underlying the models increases by one observation.

4. The formation of the regression equation complex is completed when all observations are included in the last model.

The regression equations were developed using stepwise regression analysis (SRA) which allows forming regression equations that include only statistically significant indicators when predicting the skin factor S. The methodology and examples of using stepwise regression analysis to solve various oil field problems are presented in papers[10–16].

A total of 231 regression equations were constructed. It was found that the K_p indicator was used to construct 198 equations, K_{pr} – 98, K_o – 121 and N_{il} – 70 equations. Free terms and angular coefficients for the used parameters depending on the number of observations underlying the equations are characterized by a complex distribution pattern. The obtained dependencies are visualized on dependence graphs describing the equation member values on the maximum value of the observations skin factor on which basis the equations were formed (Fig. 1).

According to the graph of the change in the free terms of the equation (see Fig. 1, *a*), it was established that within the correlation field at the visual level two trajectories of change in this parameter are observed separated by the value $S = -4$. At $S < -4$ the values of the free terms increase from -12 to -4 with a local decrease to –6.2 and a further stable increase in the values of the free term to –4. Upon reaching $S = -4$ the values of the free term decrease which indicates the inclusion in the equation of observations where the process of equation formation differs from previous observations. Further, at values of $S > -3.00$, the trajectory is again characterized by a stable increase in the values of the free terms from –6 to 0.5, with a gradual decrease in the intensity of the increase.

The graph of the change in the angular coefficients at K_p (see Fig. 1, *b*) shows that the angular coefficients at K_p change along a "dome-shaped" trajectory. At values of $S < -4$ an increase in the angular coefficient at K_p is observed, at values of $S > -4$ – a decrease. This indicates that at $S < -4$ there is an increased influence of K_p on the value of S. At $S > -4$, the influence of K_p on S begins to decrease intensively.

The graph of the change in the angular coefficients at K_{pr} (see Fig. 1, *c*) shows that with a change in the values of S, the values of the coefficients at K_{pr} change insignificantly. This indicates that the influence of the K_{pr} values on S over the entire range is significantly less than K_p.

The graph of the change in the angular coefficients at K_o (see Fig. 1, *d*) shows that with a change in the values of S, the values of the coefficients at K_o have positive values of almost all the constructed models which mainly change in the range of 0.0–0.02. According to the graph of the change in the angular coefficients at N_{il} (Fig. 1, *d*), it was established that at $S < -4$, the parameter N_{il} is included in the equations in isolated cases, and at $S > -4$, it is present in almost all equations.

According to the graph of the change in the values of the coefficients R^2 (Fig. 1, *e*), we see that with an increase in the values of S, the values of the coefficients R^2 change along a trajectory within which two sections are distinguished. The boundary between these sections can be drawn at $S = -4$. At $S < -4$, with an increase in the values of S, an intensive decrease in R^2 occurs along a complex trajectory. At $S > -4$, on the contrary, R^2 increases along a simpler trajectory. Thus, based on the results of the stepwise regression analysis, the original sample was divided into two classes: for $S < -4$ – class 1, for $S > -4$ – class 2.

For a more complete statistical analysis, a comparison of the distributing the values of the indicators belonging to different classes was performed using the Pearson χ^2 criterion which is calculated using the following formula [17–19]:

$$\chi^2 = N_1 N_2 \sum_{i=1}^{e} \frac{1}{M_1 + M_2} \left(\frac{M_1}{N_1} - \frac{M_2}{N_2} \right)^2, \qquad (1)$$

where is the number of indicator values for the 1st and 2nd classes, respectively; is the number of values that fall within the specified interval for the 1st and 2nd classes, respectively; e is the number of intervals for the studied indicators. Comparing the average values of the selected classes parameters was also made using Student's t-test [20–24] which is calculated using the formula:

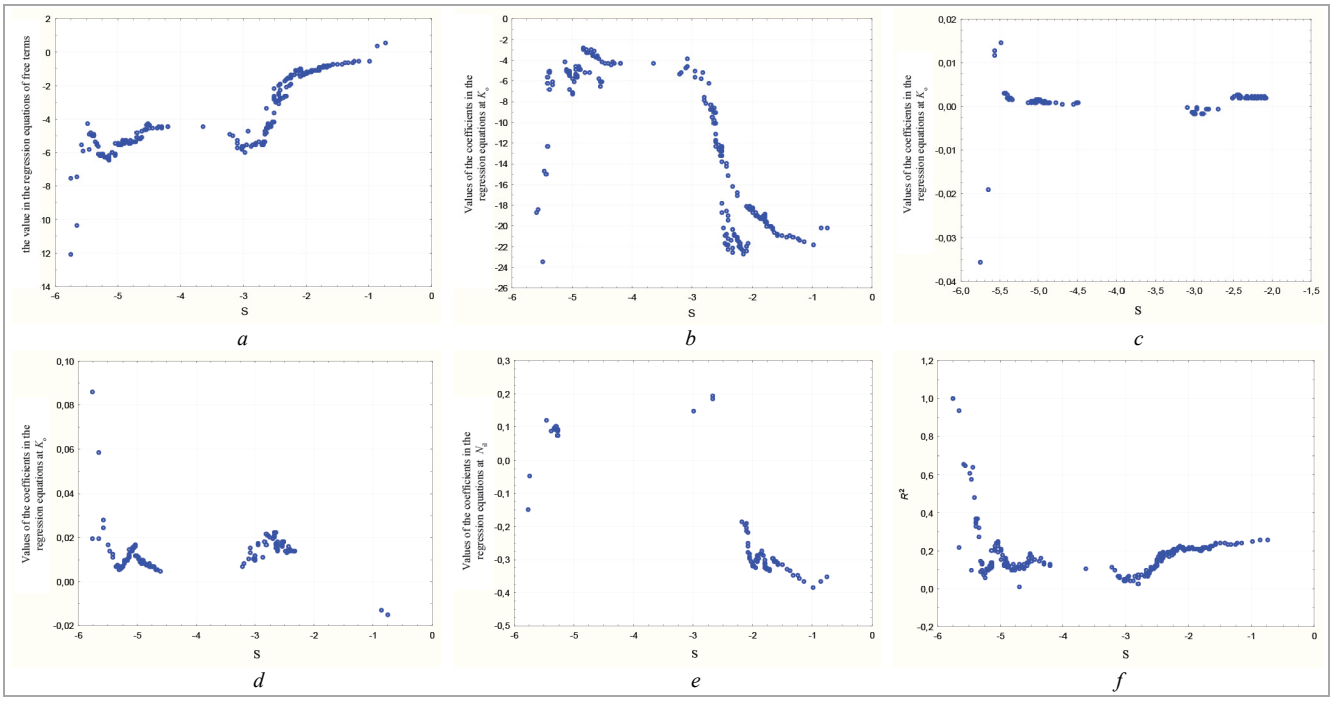

Fig. 1. Changes in the values of: *a* – free terms; *b* – angular coefficients for K_o; *c* – angular coefficients for K_{pr}; *d* – angular coefficients for K_o; *e* – angular coefficients for N_{il}; *f* – coefficients R^2

Table 1

Results of class comparison using Pearson's criterion and Student's *t*-test

Parameter	$S < -4{,}00$ Av.value ± SD	$S > -4{,}00$ Av.value ± SD	χ^2- Pearson's criterion *p*-level of significance	Student's *t*-test *p*-level of significance
K_o, unit fr.	0.180 ± 0.032	0.105 ± 0.024	44.52973 0.000000	6.996138 0.000000
K_{pr}, μm^2	50.1 ± 95.5	9.7 ± 20.7	22.10853 0.000016	4.773860 0.000003
K_o, %	85.0 ± 7.6	80.7 ± 9.6	12.62259 0.001816	3.609743 0.000376
N_{ib} m	1.15 ± 0.49	1.01 ± 0.38	5.904172 0.052231	2.421855 0.016213

$$t_p = \frac{|X_1 - X_2|}{\sqrt{\frac{1}{n_1} + \frac{1}{n_2}\left(\frac{(n_1-1)S_1^2 + (n_2-1)S_2^2}{n_1 + n_2 - 2}\right)}}, \quad (2)$$

where X1, X2 are the average values of the indicators for the 1st and 2nd classes, respectively, and are the dispersions of the indicators by classes. The difference betweenthe average values is considered statistically significant (the hypothesis is confirmed) if the calculated value of the *t*-criterion is greater than the theoretical one: $t_p > t_T$. If $t_p < t_T$, the hypothesis is rejected; there are no differences in the average values. The values of t_T are determined depending on the amount of data compared and the significance level ($\alpha = 0.05$). The results of class comparison are presented in Table 1.

It is clear from this that within the selected classes, the distribution densities for all parameters differ statistically. It was also established that for all parameters, the differences in average values are statistically significant.

Construction of probabilistic models for determining the class of interlayer

After this, to reduce the studied parameters to a single dimension (probability), linear probability models belonging to class 1 ($S < -4$) were constructed.

To construct probability models the optimal values of the variation intervals are first determined which are calculated using the Sturgess formula [25, 26]:

$$\Delta X = \frac{X_{max} - X_{min}}{1 + 3.322\Delta \lg N}, \quad (3)$$

where X_{max} is the maximum value of the indicator, X_{min} is the minimum value of the indicator, N is the number of observations. In each interval, the frequencies are determined:

$$P(X_j | W_k) = \frac{N_k}{N_q}, \quad (4)$$

where $P(X_j|W_k)$ – frequency in the k-th interval for classes W_q ($q = 1$ corresponds to the 1-st class, and $q = 2$ corresponds to the 2-nd class); N_k is the number of cases of the $P(X)$ indicator in the k-th interval; N_q is the sample size for the 1-st and 2-nd classes. The distribution of frequencies in the studied classes by the K_p indicator is given in Table 2.

Based on the analysis of the data in Table 2 it was found that there is a shift in the frequencies of occuring values by classes when the variation intervals change. For $S < -4$ the values are in the range of 0.06–0.24 fractions of a unit, with a modal interval of 0.10–0.12 fractions of a unit.

Table 2

Distribution of frequencies K_p by classes

Object class	variability K_o interval, unit fr.								
	0.06–0.08	0.08–0.10	0.10–0.12	0.12–0.14	0.14–0.16	0.16–0.18	0.18–0.20	0.20–0.22	0.22–0.24
Class 1 (S < –4.00)	0.010	0.142	0.306	0.234	0.132	0.102	0.051	–	0.020
Class 2 (S > –4.00)	0.148	0.303	0.288	0.185	0.051	0.022	–	–	–

Table 3

Individual probability models

Parameter	Probability equation for class 1 (S < –4)	Range of indicators variation	Range of probability variation
K_o, unit fr.	$P(K_p) = 0.127 + 3.2527\ K_p$	0.061–0.237	0.325–0.897
K_{pr}, μm²	$P(K_{pr}) = 0.476 + 0.0011\ K_{pr}$	0.258–399.0	0.476–0.914
K_o, %	$P(K_o) = -0.459 + 0.0117\ K_o$	47.4–95.5	0.095–0.658
N_{il}, m	$P(N_{il}) = 0.310 + 0.1751\ N_{il}$	0.02–3.14	0.313–0.859

For wells with $S1$ > –4.00 from 0.06 to 0.18 fractions of a unit, a decrease in the range of values is observed, the mode is in the interval of 0.08–0.10 fractions of a unit. All this shows that the S values depend to a large extent on the K_p value. Then, in each interval the conditional interval probabilities belonging to class 1 are calculated using the formula:

$$P\left(W_q|X_j\right)_k = \frac{P\left(X_j|W_1\right)_k}{P\left(X_j|W_1\right)_k + P\left(X_j|W_2\right)_k}, \quad (5)$$

where $P\left(W_q|X_j\right)_k$ is a conditional interval probability belonging to a variable X_j in the k-th interval to class.

Then the interval probabilities belonging to this class are compared with the average interval K_p values. Based on these data a probability model belonging to class 1 is constructed using regression analysis.

If necessary, the constructed models are adjusted based on the condition that the average value of probabilities for class 1 (S < –4) should be greater than 0.5, and for class 2 (S < –4) less than 0.5. Detailed information on the construction and use of individual probability models is presented in papers [27–36].

Using the above-described method probability models were obtained for all parameters (Table 3).

Graphically, probability models for all parameters are presented in Fig. 2.

To take into account the probabilities obtained for individual models a complex criterion P_{comp} which is determined by the formula [37–42] was developed for all parameters as a whole:

$$P_{comp} = \frac{\prod P_i}{\prod P_i + \prod\left(1 - P_i\right)}, \quad (6)$$

where P_i is the individual probability of the parameters.

After calculating the complex probability P_{comp} of assignment to the 1st class for all observations, regression equations were constructed where the complex probability P_{comp} was chosen as the dependent variable and the probabilities for individual models were chosen as independent variables. The order of forming the complex probability model by steps is presented in Table 4.

Comparison of the values of the obtained complex probabilities P_{comp} of the selected classes at each step is given in Table 5.

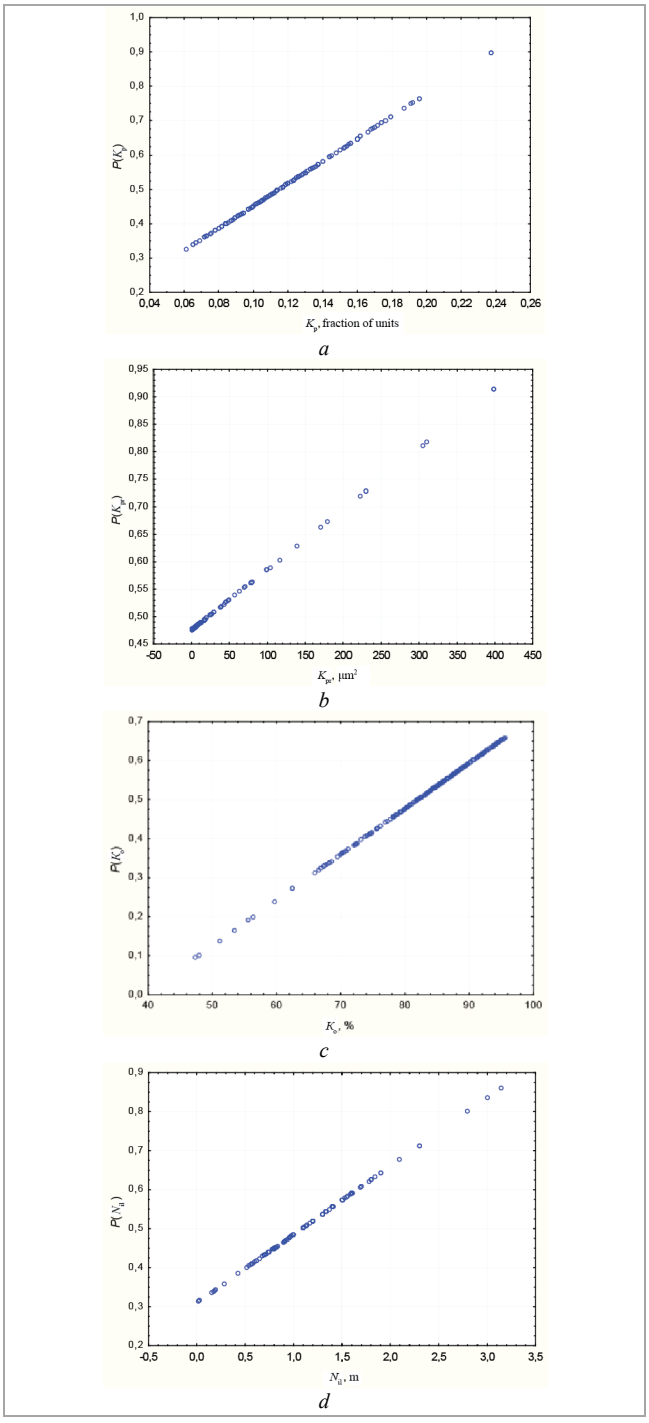

Fig. 2. Individual probability models by parameters: *a* – K_p; *b* – K_{pr}; *c* – K_o; *d* – N_{il}

Table 4

Regression equations for different m

m	Free term of regression	Coefficients for characteristics in regression equations, the order of inclusing indicators in regression equations is given in brackets				R	p
		$P(K_p)$	$P(K_{pr})$	$P(K_o)$	$P(N_{il})$		
m = 2	–0.269	1.079046(1)	0.449482(2)			0.993	<0.00000
m = 3	–0.621	1.029376(1)	0.312473(2)	0.892352(3)		0.995	<0.00000
m = 4	–0.933	1.014109(1)	0.194175(2)	0.878614(3)	0.773591(4)	0.985	<0.00000

Table 5

Comparison of the values of the obtained complex probabilities P_{comp} of the selected classes at each step

m	Classes of allocated wells P_{comp}		Criteria $\frac{\chi^2}{p}$	Criteria $\frac{t}{p}$
	where S >–4,00	при S< –4,00		
m = 2	0.567 ± 0.155	0.456 ± 0.093	43.32163 0.000000	7.177429 0.000000
m = 3	0.593 ± 0.188	0.447 ± 0.159	47.68480 0.000000	7.387939 0.000000
m = 4	0.601 ± 0.190	0.439 ± 0.179	50.09144 0.000000	7.626951 0.000000

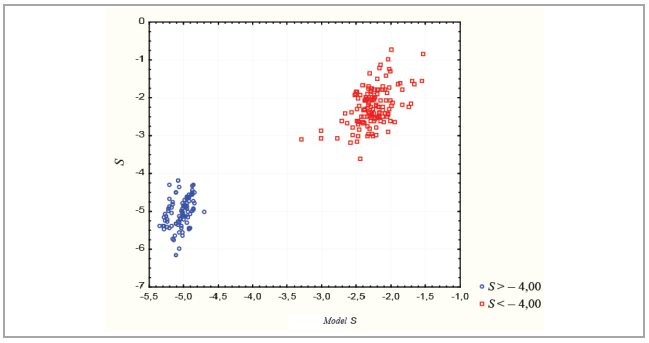

Fig. 3. Comparing actual and model values of the skin factor

It follows from Table 5 that the difference in the values of P_{comp} for the selected classes increases consistently with the increase in the number of parameters in the equation. Thus, it is shown that in order to predict the values of the skin factor S, each selected class should be considered separately.

Building Mathematical Models for Skin Factor Forecasting

Next, for each class, using the step-by-step regression analysis method, predictive models of the skin factor S are constructed. The regression equation for the 1st class has the form:

$$S_1 = -4.473 - 4.256 \cdot K_p, \quad R = 0.348,\ p = 0.0004,\ \sigma = 0.3687. \tag{7}$$

Only one parameter K_p is involved in the equation. The parameters K_o, K_{pr} and N_{il} are not included in the model due to their low significance for predicting the skin factor in this group. The regression equation for the 2nd class has the following form:

$$S_2 = -0.653 - 0.005 \cdot K_{pr} - 0.019 \cdot K_o, \quad R = 0.48,\ p = 0.0000,\ \sigma = 0.4494. \tag{8}$$

At the first step of constructing the model the K_o indicator was used, at the second it was K_{pr}. The values of the R coefficients describing the strength of statistical relationships changed as follows: 0.436, 0.480. The K_p and N_{il} parameters were not included in the model due to their low significance for predicting the skin factor in this group.

The graphical comparing the actual and model values of the skin factor are shown in Fig. 3.

It can be seen from this that positive correlations are observed for the selected groups, and the model S values are located within the selected class boundaries.

Moreover, for comparison with the obtained models by class, a basic model was constructed based on the use of all observations, regardless of their belonging to the groups. The regression equation of the basic model is as follows:

$$S = -0.534 - 20.163 \cdot K_{pr} - 0.352 \cdot H_{pr} - 0.015 \cdot K_o,\ R = 0.508, < 0.0000,\ \sigma = 1.258. \tag{9}$$

To compare the base model and the model with the allocation of classes of mathematical models, the average absolute and average relative forecast errors were calculated [43–45]. The average absolute error expresses the degree of discrepancy between the actual and predicted values in absolute values and is calculated using the formula:

$$\bar{E}_{abs} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|, \tag{10}$$

where y_i – fact parameter, $\hat{y}_i$ – predicted parameter, n – number of observations.

The average relative error expresses the degree of discrepancy between actual and predicted values as a calculated percentage using the formula:

$$\bar{E}_{rel} = \left(\frac{1}{n}\sum_{i=1}^{n}\frac{\left|y_i - \hat{y}_i\right|}{y_i}\right)\cdot 100\ \% \tag{11}$$

Table 6

Comparison of models by metrics

Model	Mean absolute error, un.	Average relative error, %
Basic model	1.07	37.99
Model by class	0.33	13.17

The results of calculating these errors for each model are presented in Table 6.

From this it was established that the class model has higher accuracy compared to the base one.

Conclusion

1. The statistical analysis showed that in the Bashkirian deposits of the oil fields of the Perm region two classes of reservoir layers can be distinguished where the skin factor depends on various factors.

2. A probabilistic-statistical model is proposed that allows us to classify the studied foam plastic based on its characteristics into one of the classes.

3. A mathematical model is constructed for each of the classes allowing us to predict the skin factor after acid treatment.

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