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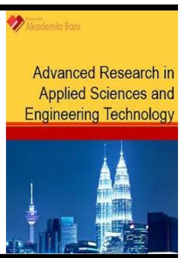

Time Estimation of Gas-Water Contact Lift using Response Surface Analysis in Yamburg Gas Field Conditions

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ABSTRACT

The Yamburg oil and gas condensate field, like many northwestern fields, is at the final stage of production. The consequence is that the large amount of formation water in the inflow may accumulate in particular in well bottom hole. The response surface analysis is used as a new technique for gaining detailed understanding of the relationships between combinations of two predictor variables and a result variable. This approach was applied to the Yamburg field in order to estimate the time of gas-water contact lift considering the lithological characteristics of the reservoirs. The results of the predicted gas-water contact time were compared to the expected gas-water contact time, the data of which were considered for the study. Using the parameters of the model as well as the three-dimensional response surface, which was built to facilitate and improve the interpretation of the results, it was possible to predict the gas-water contact time under certain conditions.

Keywords:
Gas-water contact; response surface analysis; time prediction; Yamburg; gas field; lithological characteristics

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1. Introduction

1.1 Lithology

For the Yamburg oil and gas condensate field (YOGCF), according to the lithological description and physical properties (tab. 1), five groups of gas-producing reservoirs are distinguished. The reservoir-non-reservoir boundary passes through the rocks of group 5 in terms of filtration-capacitive parameters [1]:

Reservoirs of group 1 are represented by three types of sandstones - super-reservoirs, reservoirs with improved porosity and filtro-capacitive properties (reservoir properties) and reservoirs with poor reservoir properties (three-modal porosity distribution). The boundaries of group 1 by porosity are 0.32 - 0.41 (Φavg - the average value of the porosity coefficient is 0.35); by residual water saturation 0.05 - 0.18 (Swr,avg - average value of the residual water saturation coefficient is 0.155)

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(unimodal distribution); by granulometry with grain size <0.01 mm, distribution of the clay content function in the range of 5 - 15%.

The second group is represented by reservoirs with a significant range of changes in capacitive properties (0.24 - 0.37) (multimodal distribution of porosity and residual water saturation), which once again indicates a mixed composition of this group - siltstones and interbedded siltstones with sandstones and clays (groups 1, 3, 5). The parameters of this group can be estimated only by a homogeneous component – siltstones. According to the granulometry corresponding to siltstones, there is a regular shift in the distribution of the clay content function (with a grain size of <0.01 mm) in the range of 10-30%.

Reservoirs of group 3 are represented by a unimodal distribution of porosity and water saturation - this is due to the thin interlayering of mainly sandy-siltstone components on the scale of the core sample; the estimation of the reservoir properties of this group is quite possible due to the quasi-uniformity on the scale of core samples. According to granulometry, there is a regular shift in the distribution of the clay content function (with a grain size of <0.01 mm) in the range of 15-30%.

Reservoirs of group 4 are represented by a two-modal distribution of porosity and water saturation - this is due to the inclusion of individual clay samples (group 5) and samples with thin interlayering of clay-silt components on the scale of the core sample (group 3). Evaluation of reservoir properties for this group does not make sense because the parameters of groups 3 and 5 are defined. According to granulometry, there is no regular shift in the distribution of the clay content function (with a grain size of <0.01 mm) and is in the range of 15-30%.

Reservoirs of group 5 are represented by a three-modal distribution of porosity and water saturation - this is due to the inclusion in this group, along with clay samples, of a number of samples represented by interlayering of clay-silt components (groups 3, 4). The estimation of reservoir properties for this group is meaningful only for the clay component. The reservoir properties of the clay component Φavg and Swr,avg are respectively 0.192 and 0.82. According to granulometry, there is a regular shift in the distribution of the clay content function (with a grain size of <0.01 mm) and is in the range of 30 - 45%.

Table 1
Boundaries of collector groups by capacitive parameters

Group number	Collector characteristics	Lithology	Φmin.	Φmax.	Φavg.	Swr,avg
1a	Super collector	Weakly cemented sandstone	0.39	0.45	0.396	0.116
1b	Improved	Sandstone	0.36	0.39	0.371	0.135
2	Good	Silty sandstone	0.32	0.36	0.34	0.168
3	Deteriorated	Siltstone	0.28	0.32	0.301	0.272
4	Interbedding of deteriorated reservoirs with rocks having an initial gradient	Interbedding of sandstones, siltstones and clayey siltstones	0.24	0.28	0.258	0.45
5	Interbedding of initial gradient reservoirs and non-reservoirs	Interbedding of sandstones, clayey siltstones and clays	0.18	0.24	0.212	0.74

1.2 Polynomial Regression with Response Surface Analysis

Response surface analysis has been applied in various fields of science [2-9], but remains an insufficiently substantiated question especially on the issue of flows in underground environments.

The method is a relatively new technique [10] that can provide detailed insight into the relationships between combinations of two predictor variables and an output variable by plotting the results of polynomial regression analysis in 3D space [11].

It should be noted that the model includes all possible second-order terms. This is useful because skipping members implies information that certain types of surfaces cannot be encountered, which would be unthinkable without skipping members. Such cases are not common. When such information is available, research can usually be conducted on a more rigorous theoretical basis.

This method has more informative potential than, for example, traditional regression analysis, and is promising for application to a wide range of research questions.

Based on their respective values of porosity and residual water saturation coefficients, two predictors that relate to our question have been identified. These two predictors are, on the one hand, an assembly of the first three groups of reservoirs, which we will call high porosity reservoirs (HPR), and on the other hand, an assembly of the last two groups of reservoirs, which we will call low porosity reservoirs (LPR).

According to several authors [12], the assumptions necessary to implement the method have been met. Any difference in the position of the two predictor variables was understood in a meaningful way because the predictors were commensurable; that is, they represent the same conceptual area.

The second assumption, which was fulfilled, states that the predictor variables must be measured on the same numerical scale in order to determine their degree of fit [12].

In conclusion, as with any regression method, all the usual assumptions of multiple regression analysis must also be met (for a list of these assumptions, see [13]).

In the response surface analysis approach, polynomial regression is performed first. The general form of the equation for testing relationships using polynomial regression is as follows

$$Z = b_0 + b_1X + b_2Y + b_3X^2 + b_4XY + b_5Y^2 + e \quad (1)$$

where Z – the dependent variable (time interval, in days), X is predictor 1 (width of high porosity reservoirs, in meters), and Y is predictor 2 (width of low porosity reservoirs, in meters).

Thus, the original variable is determined by the regression of two predictor variables (X and Y), the interaction between the two predictor variables (XY), and the square of the terms for each of the two predictors (X2 and Y2).

Using polynomial regression and subsequent analysis of the response surface, one can inspect:

(1) How is the correspondence (agreement) between the two predictor variables (X and Y) related to the final variable (Z), (2) how is the degree of mismatch (discrepancy) between the two predictor variables (X and Y) related to the outcome (Z), and finally (3) how is the direction of discrepancy between the two predictor variables (X and Y) related to the final variable (Z).

Rather than directly interpreting the results of the polynomial regression analysis, the coefficients from the analysis are used to explore what is called the “response surface model” [14], [15], which is presented as a three-way visual representation of the data to facilitate interpretation.

2. Data Collection

A total of 41 wells were selected, distributed across all well clusters, and their data was processed. In this study, a model was developed to predict the timing of gas-water contact levels.

For each well, the thicknesses of different geological formations were measured, citing their differences at the lithological level. These were the thicknesses of different layers crossed by the gas-water contact during a certain period of time (in the number of days). 170 intervals were identified as valid and were considered as raw data.

All geological formations, divided into the 5 lithological groups, were distributed. For each given time interval, all 5 groups of geological formations are not necessarily represented.

3. Method Execution and Results

Before performing the polynomial regression analysis, a test was performed to find out how many time intervals would be related to discrepancies between the two predictors, so that the baseline of discrepancy in the sample was presented [16].

With this information, there was an idea of the discrepancies that exist in the sample, how many and in which direction. Since many intervals were found to have discrepant values (for example, HPR higher than LPR or vice versa), the practical value of studying how the discrepancies affect the outcome variable was great. A total of 36.5% of HPR and 4.7% of LPR were considered inappropriate. This means that 58.8% of the data was in agreement.

Since we made sure that there are discrepant values in our sample, the polynomial regression was performed [17]. At first, the predictors (HPR and LPR) were centered around the midpoint of their respective scales [14], to simplify interpretation and reduce the likelihood of multicollinearity [12], [18-22]. Then, three new variables were created: (a) the square of the centered HPR variable; (b) the cross product of the centered variable HPR and LPR; and (c) the square of the centered LPR variable. Then polynomial regression analysis was performed. This was done by regressing the final variable (time interval) against the centered predictor variables (HPR and LPR), the square of the centered HPR variable, the cross product of the centered variable HPR and LPR, and the square of the centered variable LPR.

Rather than examining the regression coefficients, as would be done in a conventional regression analysis, if R^2 (the variance of the original variable explained by the regression equation) is significantly different from zero, the polynomial regression results are estimated against the four values of the surface test: a_1, a_2, a_3 and a_4 [12]. The results of the analyzed samples are shown in Table 2. The slope of the line of ideal agreement (HPR = LPR) in relation to the displacement time of the gas-water contact (TGWC) is defined as $a_1 = (b_1 + b_2)$, where b_1 – non-standard beta coefficient for centered HPR variable, and b_2 – non-standard beta coefficient for centered LPR variable. The curvature along the line of ideal fit with respect to TGWC is estimated by calculating $a_2= (b_3 + b_4 + b_5)$, where b_3 – non-standard beta coefficient for the square of the centered HPR variable, b4 – non-standard beta coefficient for the cross product of the centered variable HPR and LPR, and b5 – non-standard beta coefficient for the square of the centered LPR variable. The curvature of the line of inconsistency with respect to TGWC, indicating the degree of discrepancy between the HPR, LPR and the result of TGWC, is estimated by calculating $a_4 = (b_3 - b_4 + b_5)$. The slope of the discrepancy line with respect to the TGWC, indicating the direction of the divergence (where HPR higher than the LPR or vice versa), is estimated by calculating $a_3 = (b_1 - b_2)$.

The plot and calculated surface values have been interpreted with three concepts in mind. We considered, firstly, how the agreement in the HPR and LPR is related to the TGWC, secondly, how the degree of discrepancy between the HPR and the LPR is related to the TGWC, and thirdly, how the direction of the discrepancy between the HPR and the LPR is related to the TGWC.

Table 2
Coefficients and parameters of the model

	TGWC (displacement time of the GWC)
Variables	b (se)
Constant	1057.881 (91.263)***
HPR (high porosity reservoirs)	102.21 (26.372)***
LPR (low porosity reservoirs)	163.032 (58.11)**
HPR^2	0.77 (2.373)
HPR x LPR	-23.902 (8.468)**
LPR^2	4.917 (15.037)
R^2	0.336***
Surface tests	
a_1	265.24***
a_2	-18.22*
a_3	-60.82
a_4	29.59

Note: N = 170
b – nonstandard regression coefficient, se – standard error
* p < 0.1; ** p < 0.01; *** p < 0.001

To facilitate and improve the interpretation of the results, a three-dimensional response surface was built and its features were investigated (Fig. 1).

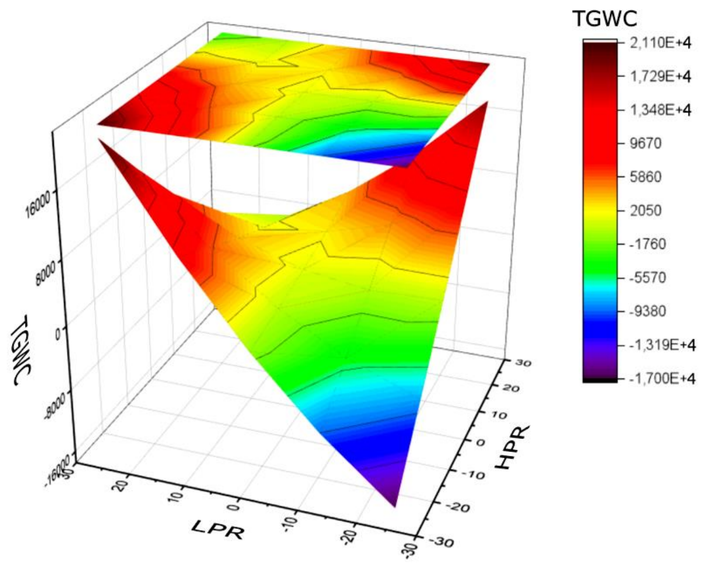

Fig. 1. Displacement time of the GWC (TGWC) in relation to the discrepancies of the HPR and LPR

The congruence hypotheses argue that the agreement between HPR and LPR should positively (or negatively) influence the TGWC. Since we were interested in whether the agreement between HPR and LPR could lead to the prediction of the TGWC, we compared the position of the ridge with a line in the XY plane (HPR-LPR), which contains all combinations of the predictors in agreement HPR = LPR. Therefore, we expressed the projection of the first major axis in the form of a linear equation connecting Y with X [12,23]:

$$Y = p_{10} + p_{11}X \tag{2}$$

The p_{10} and p_{11} values can be computed from the estimated coefficients b_1 to b_5 in the polynomial regression equation. The line of perfect agreement – $Y = 0 + 1X$. The calculated p_{10} and p_{11} values are -1.19 and 16.67, respectively. These values do not suggest that the HPR and the LPR are in agreement, as p_{10} and p_{11} should be almost equal to 0 and 1 respectively.

From the interpretation of the degree of discrepancy between HPR and LPR, we came to the conclusion that in the direction of divergence (where X = -Y), the surface has a convex shape due to the value of a_4, which is high and positive (29.59).

The assumption that a significant negative a_3 should indicate that the TGWC is higher when the agreement is such that the LPR is higher than the HPR is attested. However, in the case of this study, the result also suggests that when the HPR was higher than the LPR, the TGWC could have been higher, which does not really reflect reality. This weakness of the method led to some incorrect prediction (Fig. 2).

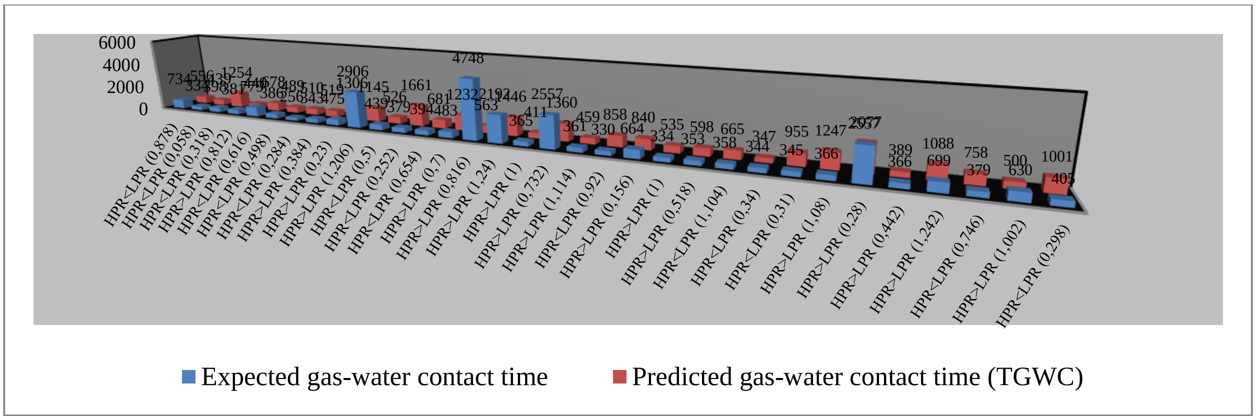

Fig. 2. The results of the predicted gas-water contact time (TGWC) compared to the expected gas-water contact time

It was found that the difference between the actual expected time and the predicted time is small for forecasts less than 1000 days.

4. Conclusions

Data collection, which constituted the very first phase of the task, was carried out on a large number of wells. It was observed that several factors may have contributed to the emergence of inaccuracies in the final results. For some gas-water contact (GWC) measurements, inconsistencies were sometimes observed, thus representing a longer displacement time for GWC in permeable formations and vice versa.

Over several intervals of geological formations, the GWC level was measured with uncertainty from the field.

The lack of additional data on the possible causes of the sudden or delayed rise in the GWC was an obstacle to understanding and interpreting this phenomenon. With data such as structural geology, water and gas flows, more detailed inferences and possibly more complete models can be drawn.

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