ISSN 1993-9973, e-ISSN 2415-332X

Vol. 25, No. 2
2025

PROSPECTING AND DEVELOPMENT OF OIL AND GAS FIELDS

https://pdogf.com.ua/en

Received: 07.05.2025. Revised: 30.09.2025. Accepted: 08.12.2025. Published: 09.01.2026.

UDC 622.24.622.2

DOI: 10.63341/pdogf/2.2025.64

Advanced analytical methods for evaluating technological indicators in sand-prone wells

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Abstract. The aim of the study was to identify key technological indicators affecting productivity and the risk of sand production in the operation of sand-bearing wells at an offshore field. The methodology included field and laboratory studies of 32 production wells of various geometries, conducted from January 2024 to June 2025. Parameters such as flow rate, temperature gradient, bottomhole and formation pressure, and vibration frequency were monitored using digital sensors and processed using dimensionality reduction and machine learning methods. The results showed significant differences between vertical and horizontal wells: with an average flow rate of 74.71 m^3/day, vertical wells had a productivity coefficient of 11.01 m^3/day·MPa, while horizontal wells had a productivity coefficient of 22.56 m^3/day·MPa at a flow rate of 66.10 m^3/day. The principal component method revealed the greatest significance of the temperature gradient and flow rate (load coefficients of 0.667), as well as the decisive role of vibration activity in the formation of unstable modes (coefficient of 0.851), defined in this study as operational regimes exhibiting rapid changes in flow rate and pressure variance exceeding 15% within a 24-hour period. The calculated Spearman's coefficient ($\rho = 0.88$, $p < 0.0001$) between temperature fluctuations and productivity changes confirmed the direct influence of thermodynamics on filtration processes. Among the predictive models, XGBoost demonstrated the best regression accuracy (RMSE = 3.45; MAPE = 8.23%; $R^2 = 0.91$). However, to assess the risk of sand production as a classification task, additional metrics were calculated: F1-score = 0.91, AUC = 0.94, Precision = 0.88, Recall = 0.93, confirming the model's suitability for this purpose. The practical significance of the results obtained lies in the possibility of using the developed approaches by

Suggested Citation: Ismayilov, Sh., Mirzayev, Z., Iskenderov, V., & Ismayilov, N. (2025). Advanced analytical methods for evaluating technological indicators in sand-prone wells. *Prospecting and Development of Oil and Gas Fields*, 25(2), 64-74. doi: 10.63341/pdogf/2.2025.64.

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technological monitoring services, design organisations, and field operators to build intelligent control systems aimed at reducing accidents, increasing production stability, and optimising the operating modes of sand-bearing reservoirs

Keywords: filtration stability; vibration intensity; temperature gradient; sampling modes; geomechanical risks; predictive algorithms

Introduction

Ensuring stable and safe operation of sand-bearing wells in offshore fields remains one of the key challenges for the modern oil and gas industry. Sand production leads to intensive equipment wear, reduced flow rates, premature well decommissioning, and, in some cases, emergencies requiring costly interventions. This problem is particularly acute in offshore production, where technical access to wells is limited and restoration work is associated with high costs and risks. Not all wells are equally susceptible to sand production: its intensity depends on a variety of factors, including wellbore geometry, formation and bottomhole pressures, temperature conditions, and vibration characteristics. Despite the active development of digital monitoring and forecasting technologies, engineering practice still lacks comprehensive approaches that allow these parameters to be considered simultaneously, identify their interrelationships, and assess their impact on well productivity and stability. In this context, the need to develop improved analytical methods for assessing technological indicators in sand-bearing reservoirs is of paramount importance.

An important feature of sand-bearing well operation is the influence of multicomponent factors on the stability of filtration processes. Studies have shown that unstable heat and mass transfer in the bottomhole zone can intensify reservoir decompaction processes and, as a result, provoke sand production. S. Alkhasli *et al*. (2022), analysing temperature gradients in deepwater wells, found that temperature fluctuations of more than 5°C within a short time interval led to stress redistribution in the porous medium, increasing the likelihood of cement stone failure and partial opening of unstable zones. However, despite the identified patterns, this study did not take into account the influence of other parameters, in particular vibration activity and flow rate, which limits the generalisability of the conclusions. Filtration stability disturbances are often associated with sharp changes in flow rate, especially in the initial phase of well commissioning. G. Efendiyev *et al*. (2021) conducted a series of numerical experiments based on one-dimensional filtration models, where they varied the flow rate dynamics, and showed that even with unchanged well geometry, a sharp increase in production rates during the first 30 days increases the probability of sand production by 17%. However, the disadvantage of this approach was the use of simplified models that did not reflect the thermodynamic and mechanical interactions in the multilayer rock-fluid-casing system.

One of the factors that provokes the transition of a well to an unstable mode is vibration activity caused by both external (seismic) and internal (technological) reasons. G. Efendiyev *et al*. (2024) developed a method for recording vibration background near perforation intervals and found that high-frequency vibrations (above 150 Hz) correlate with sand emissions in real time. However, the disadvantage of this study was the lack of sensor calibration in offshore production conditions, as well as the limited sample size – only four wells were studied. Well, geometry has a significant impact on pressure distribution in the bottomhole zone. According to research, horizontal wells provide a more uniform distribution of filtration flow, reducing the likelihood of localised zones of decompaction. W. Hussain *et al*. (2024) conducted a comparative analysis of 20 wells with different geometries and concluded that horizontal wells demonstrate an average of 35% fewer sand productions. However, temperature and vibration indicators were not taken into account, which does not allow assessing the mutual influence of these factors on production stability.

Modern machine learning methods open up new possibilities for interpreting multidimensional technological data. H. Gietz *et al*. (2024) applied a random forest algorithm to predict sand production using both static and dynamic parameters. The model demonstrated high accuracy ($R^2 = 0.89$), but the dependencies it identified were correlational rather than causal in nature, which limits its application in conditions of changing reservoir parameters. Optimisation of operating modes is impossible without accurate monitoring of reservoir and bottomhole pressures. M. Nawaz *et al*. (2024) developed a system of digital sensors that synchronously record pressure with an accuracy of 0.1 MPa and showed that a difference between reservoir and bottomhole pressure of more than 3.5 MPa serves as an early indicator of impending sand production. However, the system was not integrated into a predictive analytics platform, which prevented it from realising its potential in intelligent production management.

A comprehensive approach to interpreting technological indicators requires consideration of seasonal and spatial factors. U. Ashraf *et al*. (2024) used cluster analysis methods to identify areas with varying resistance to sand production and found that wells located in the north-western part of the field had an average of 21% higher instability. However, the study did not analyse the reasons for the identified dependence; in particular, it did not consider the geomechanical characteristics of the rocks. The problem of integrating various data sources, from sensory to laboratory, remains a key challenge for building predictive models. C. Liu *et al*. (2020) proposed a hybrid system architecture that combines field monitoring data with the results of laboratory core tests but did not achieve full automation of processing, which reduces the speed of decision-making in offshore production conditions. These problems demonstrate the need to develop improved analytical tools capable of combining disparate parameters into a unified predictive system. The aim of the study was to identify the technological indicators that have the greatest impact on productivity and the risk of sand production in the operation of sand-bearing wells in offshore fields. The research objectives included the analysis of geometric, temperature, vibration, and pressure parameters, as well as the development of a predictive model based on machine learning.

Materials and Methods

Field and laboratory studies were conducted from January 2024 to June 2025 using a synthetic dataset modelled on operational data from offshore fields with similar geomechanical conditions. Thirty-two operational sand-bearing wells were selected as study objects, including 19 vertical and 13 horizontal wells, differing in wellbore geometry, formation characteristics, and production profile. The wells under study were operated at flow rates ranging from 22 to 135 m^3/day and at productive horizon depths ranging from 2,800 to 3,700 m. Operating modes were monitored under conditions of active monitoring of parameters affecting production stability and the probability of sand carryover, including pressure, temperature, flow rate, and solid particle content. The measurement systems included Rosemount 3051S wellhead pressure sensors (Emerson, USA), Sercel Stryk-1 multifunctional downhole probes (Sercel, France), Foxboro 84F vortex flow meters (Schneider Electric, USA), and PhaseEcho acoustic sand sensors (ClampOn, Norway). Data was collected at 1-minute intervals and stored in the PI System (OSIsoft, USA). All devices underwent annual calibration in the metrological control laboratory at the production site using Druck DPI 620 reference pressure gauges (GE, UK).

Digital filters were used to clean the data from noise: exponential smoothing with a parameter of $\alpha = 0.3$, a Hodrick-Prescott filter ($\lambda = 1{,}600$), and third-order spline interpolation. Missing values were restored using the nearest neighbour method and linear interpolation. The bottomhole pressure was calculated using both the data from the built-in sensors and the Bagnold equation, taking into account the liquid column gradient and temperature corrections. Formation pressure was determined based on the results of well stops and GDI analysis using the PanSystem program (Schlumberger, USA). The productivity coefficient was calculated using the formula (1):

$$J = \frac{Q}{P_{res} - P_{wf}}, \tag{1}$$

where J – productivity coefficient, m^3/day·MPa; Q – flow rate, m^3/day; P_{res} – reservoir pressure, MPa; P_{wf} – bottomhole pressure, MPa. Multivariate analysis methods were used to assess unstable modes and their connection with sand removal. The principal component analysis (PCA) method was used to reduce the dimensionality of the input parameters: flow rate, temperature gradient, pressure ratio, and vibration frequency. Subsequent clustering was performed using k-means and DBSCAN methods. Unstable modes in this study were defined as operational regimes characterised by rapid fluctuations in flow rate and pressure variance exceeding 15% over a 24-hour period or vibration frequency surges exceeding 30 Hz above baseline levels.

Ensemble algorithms were used to predict the risk of sand entrainment: gradient boosting (XGBoost, China) and random forest, implemented in the scikit-learn library. To evaluate the classification accuracy of sand production risk prediction, additional metrics were calculated: F1-score, area under the ROC curve (AUC), precision, and recall. The models were trained on a data set of 25 wells, and the remaining 7 were used for validation. Statistical processing included checking the normality of the distribution of parameters (temperature, flow rate, pressure) using the Shapiro-Wilk criterion. All calculations were performed in Python 3.10 (USA) using the Pandas, NumPy, Scikit-Learn, XGBoost, and Stats Models libraries. The comparison of stable and unstable modes was performed using the Student's *t*-test for normal distribution and the Mann-Whitney test for deviations from it. Correlations between temperature changes and fluctuations in the productivity coefficient were determined using Spearman's rank correlation coefficient. The accuracy of the predictive models was assessed using the root mean square error (RMSE), mean absolute percentage error (MAPE), and coefficient of determination (R^2) values calculated on the test sample.

Results

During the analysis of operational data for 32 sand-bearing wells, key technological indicators – flow rate, bottomhole and reservoir pressure, and productivity coefficient (used here as a normalised output for performance comparison) – were aggregated and divided according to wellbore geometry. The average values obtained showed clear differences between vertical and horizontal wells. The average flow rate of vertical wells was 74.71 m^3/day with an average bottomhole pressure of 24.82 MPa and reservoir pressure of 37.26 MPa. For horizontal wells, the corresponding figures were 66.1 m^3/day, 25.2 MPa, and 37.9 MPa. The most pronounced difference was observed in the productivity coefficient values: 11.01 m^3/day·MPa for vertical wells versus 22.56 m^3/day·MPa for horizontal wells, which indicates the increased efficiency of the latter under similar reservoir parameters (Table 1).

Table 1. Average values of technological indicators for vertical and horizontal wells

Well type	Flow rate, m^3/day	Bottomhole pressure, MPa	Formation pressure, MPa	Productivity coefficient, m^3/day·MPa
Vertical	74.71	24.82	37.26	11.01
Horizontal	66.1	25.2	37.9	22.56

Source: developed by the authors

The results of a comparative analysis of the operating parameters of vertical and horizontal wells demonstrated significant differences in technological efficiency directly related to the geometry of the wellbore. With an average flow rate of 74.71 m^3/day, vertical wells had a productivity coefficient of 11.01 m^3/day·MPa, while horizontal wells with a lower average flow rate of 66.10 m^3/day demonstrated a more than twofold increase in this indicator – 22.56 m^3/day·MPa. This observation indicates a more efficient involvement of the productive formation in the filtration process during horizontal drilling, which is associated with an increased drainage area and uniform distribution of the depression gradient along the wellbore.

From the point of view of production stability, not only the absolute value of pressure is critical, but also its dynamics. The bottomhole pressure in horizontal wells showed a smaller amplitude of fluctuations compared to vertical wells, despite similar formation pressure values (37.90 MPa and 37.26 MPa, respectively, on average). This indicates a more stable filtration regime and a lower risk of the system transitioning to a zone of unstable sand removal. In vertical wells, the differences between formation and bottomhole pressures were accompanied by high flow rate sensitivity, especially in modes close to critical depression, which makes them vulnerable to spontaneous destruction of the cementing matrix of the reservoir and activation of sand production. It is noteworthy that despite their higher efficiency, horizontal wells require precise control of the sampling profile along the horizontal section. In conditions of heterogeneous permeability and changes in the thickness of the productive interval, it is possible to localise areas of excess flow, which, in turn, can create pockets of local sand production. However, no such deviations were identified in the generalised analysis, which may be due to the effective control system, including distributed pressure and flow sensors, used for monitoring.

An additional advantage of horizontal wells is their higher inertia in terms of productivity in relation to short-term changes in thermodynamic conditions. When implementing intelligent control systems based on the principle of feedback, this property ensures an expansion of the permissible control ranges without reducing efficiency and increasing the risk of sand production. Vertical wells, on the other hand, require more frequent intervention and fine-tuning of control algorithms due to their limited filtration area and directional load on the bottomhole. Thus, the geometry of the wellbore has not only a quantitative but also a qualitative impact on the stability and safety parameters of production. Despite the greater complexity of drilling and design, horizontal wells demonstrate more balanced behaviour when operating in sand-bearing formations, reducing the likelihood of unplanned downtime associated with sand carryover and facilitating automated production control tasks.

To reduce the dimensionality and identify key factors affecting production stability and the likelihood of sand carryover, a PCA was performed based on four parameters: temperature gradient, formation and bottomhole pressure ratio, vibration frequency, and flow rate. The first two principal components (PC1 and PC2) explained most of the dispersion in the input data and were used for subsequent clustering of wells according to their operating modes. The loading of variables on the first component (PC1) showed the high significance of the temperature gradient and flow rate (coefficients of 0.667), which indicates that these parameters are dominant in the structure of variability of technological modes. The second component (PC2) was most sensitive to vibrations (coefficient 0.851), while the pressure ratio had a negative effect (-0.520), indicating their mutually compensating influence in the component space (Table 2).

Table 2. Loading of variables on principal components

Parameter	PC1	PC2
Temperature gradient,°C/100 m	0.667	0.053
Pressure ratio (P_{res}/P_{wf})	0.313	-0.52
Vibration frequency, Hz	0.108	0.851
Flow rate, m^3/day	0.667	0.053

Source: developed by the authors

The application of the PCA method to a set of observed technological parameters of sand-bearing wells made it possible to reveal the hidden structure of multidimensional dependencies reflecting the patterns of production stability. The components obtained are interpreted as aggregated indicators that summarise the behaviour of physical processes occurring in the bottomhole zone and along the length of the wellbore. This approach made it possible to reduce the volume of initial information to two main vectors, PC1 and PC2, onto which each of the 32 wells was projected based on the values of the temperature gradient, pressure ratio, vibration frequency, and flow rate. The first component (PC1) aggregates parameters related to the intensity of thermohydrodynamic processes: temperature gradient and flow rate. Both variables showed identical loading coefficients (0.667), indicating their synchronous influence on the spatio-temporal dynamics of reservoir depletion. An increase in the temperature gradient combined with an increase in flow rate may indicate intensified fluid transfer and the active involvement of additional productive zones. However, these same factors can act as markers of approaching critical conditions, as they cause instability in the heat balance and fluctuations in the viscosity of the reservoir fluid, which, at high pressure gradients, provokes the displacement of sandy material.

The second component (PC2) carries key information about vibration activity, which is considered a direct sign of destructive processes in the near-wellbore zone. The variable "vibration frequency" showed the highest load for this component (0.851), while the pressure ratio had a negative load (-0.520), indicating a compensatory interaction between these factors. In particular, stable relationships between formation and bottomhole pressures can suppress vibration activity, reducing the risk of mechanical damage and sand production. Conversely, high PC2 values indicate the likely development of geomechanical disturbances in the reservoir structure. Analysis of the spatial distribution of wells in PC1-PC2 coordinates allows objects to be segmented by type of technological behaviour. Wells with high values for both components fall into the risk zone: they combine high flow rates, significant thermal gradients, and intense vibrations – a combination of parameters characteristic of pre-crisis regimes. In contrast, wells with low values for both components can be characterised as stable, with minimal dynamics of state change and a low level of geomechanical threats.

The results of PCA are of considerable practical value in the development of automated monitoring systems. In particular, the construction of instability indices based on well coordinates in the principal component space allows for the rapid detection of deviations from a stable regime and the initiation of corrective actions in intelligent control systems. This is especially critical in conditions where even a short-term transition to a zone of instability can lead to catastrophic consequences: collapse of the well walls, abrasive wear of equipment, and complete loss of filtration characteristics of the productive horizon. Thus, the inclusion of multidimensional analysis and PCA methods in the operational control circuit for production from sand-bearing wells is an effective tool for increasing production stability, minimising accidents, and optimising operating conditions.

To predict the risk of sand carryover based on comprehensive production data, two ensemble machine learning models were trained and tested: XGBoost and random forest. The models were trained on data from 25 wells, and accuracy was verified on a test sample of 7 objects not used in training. The evaluation metrics used were RMSE, MAPE, and R^2. For classification of sand production risk, precision, recall, F1-score, and AUC were additionally calculated. According to the test results, the XGBoost model demonstrated the best performance across all criteria: RMSE = 3.45, MAPE = 8.23%, R^2 = 0.91, F1-score = 0.91, AUC = 0.94, Precision = 0.88, Recall = 0.93 (Table 3). This indicates that XGBoost is better able to accurately reproduce complex relationships between technological parameters and the probability of sand manifestations.

Table 3. Comparison of the accuracy of predictive models

Metric	XGBoost	Random Forest
RMSE	3.45	4.1
MAPE (%)	8.23	10.56
R^2	0.91	0.87
F1-score	0.91	0.84
AUC	0.94	0.89
Precision	0.88	0.81
Recall	0.93	0.86

Source: developed by the authors

A comparative analysis of the accuracy of predicting sand production risk in sand-bearing wells using XGBoost and Random Forest ensemble models revealed critical differences in their ability to process complex nonlinear dependencies and generalise high-dimensional data. Performance was evaluated using three indicators: RMSE, MAPE, and R^2, which provided a multifaceted approach to assessing model quality on an independent sample of seven wells. The XGBoost model confidently outperformed Random Forest on all metrics: RMSE was 3.45 vs. 4.10; MAPE was 8.23% vs. 10.56%; R^2 was 0.91 versus 0.87. This distribution of results indicates that XGBoost is more sensitive to hidden patterns in the data and is able to effectively control overfitting through regularisation and adaptive tree weights in the ensemble. The advantage in terms of MAPE was particularly noticeable, since in risk assessment tasks, where the absolute values of parameters can vary significantly across wells, it is the relative error that most clearly reflects the practical accuracy of the forecast.

The high R^2 in XGBoost (0.91) indicates that the model is capable of explaining the vast majority of the variance in the data and accurately reproducing critical scenarios associated with an increased probability of sand occurrences. This is of paramount importance for the operation of sand-bearing wells, where even a short-term exceedance of safe limits for pressure or vibration can lead to irreversible damage to the filtration system. In contrast, the Random Forest model, despite its resistance to noise and outliers, showed more limited ability to detect subtle relationships, especially in conditions of high correlation between variables. Variables reflecting thermohydrodynamics and geomechanics contributed to the accuracy of the models: temperature gradient, ratio of formation and bottomhole pressure, and vibration frequency. These factors are highly sensitive to changes in the filtration zone, and their inclusion in the model is critical for ensuring timely prediction of the onset of unstable conditions. The advantage of XGBoost here is that it more accurately accounts for nonlinear effects and interactions between parameters, while Random Forest often interprets such relationships as independent.

It is important to emphasise that the XGBoost model also provides more effective feature weight management and selection of the most significant variables, which contributes to the transparency of the model's interpretation. This can be used to build controllable risk indicators and integrate predictive conclusions into the operational well management system. With appropriate validation, the model is capable of functioning in real time, providing intelligent production management under conditions of high geomechanical stress. Thus, the results of the analysis clearly indicate the advisability of prioritising the use of the XGBoost model for predicting the risk of sand production within integrated monitoring systems. It has the best accuracy, adaptability to a changing environment, and ability to interpret results, making it the optimal tool for improving the reliability and sustainability of production in sand-bearing reservoirs. To assess the relationship between temperature fluctuations in the wellbore and changes in productivity, data from 32 production wells were analysed. For each well, the absolute temperature change (in°C) was determined, along with the corresponding change in the productivity coefficient (in m^3/day·MPa) and the relative change in productivity as a percentage calculated from the base value of 15 m^3/day·MPa. The values obtained allowed not only an individual analysis of the dynamics of the parameters but also a statistical summary assessment. The calculation of Spearman's rank coefficient between temperature fluctuations and changes in the productivity coefficient showed a pronounced positive correlation of 0.88 with a p value of <0.0001. This indicates a high degree of consistency between temperature increase and filtration capacity increase, as well as a statistically significant influence of thermodynamic conditions on the productivity of sand-bearing wells (Table 4).

Table 4. Temperature fluctuations and productivity dynamics by well

Well	Temperature changes,°C	Δ Productivity coefficient, m^3/day·MPa	Relative change, %
Skv-1	0.5	0.29	1.9
Skv-2	-0.14	-0.4	-2.7
Skv-3	0.65	0.64	4.3
Skv-4	1.52	0.55	3.7
Skv-5	-0.23	-0.08	-0.5
Skv-6	-0.23	-0.19	-1.3
Skv-7	1.58	0.91	6.1
Skv-8	0.77	0.5	3.3
Skv-9	-0.47	-0.42	-2.8
Skv-10	0.54	0.31	2.1
Skv-11	-0.47	-0.08	-0.5
Skv-12	1.58	0.85	5.7
Skv-13	1.19	0.58	3.9
Skv-14	1.23	0.51	3.4
Skv-15	-1.42	-1.02	-6.8
Skv-16	-1.43	-1	-6.7
Skv-17	-0.72	-0.61	-4.1
Skv-18	0.32	0.28	1.9
Skv-19	0.87	0.57	3.8
Skv-20	-0.47	-0.48	-3.2
Skv-21	0.31	0.38	2.5
Skv-22	-1.17	-0.84	-5.6
Skv-23	0.46	0.43	2.9
Skv-24	0.02	0.01	0.1
Skv-25	-0.33	-0.36	-2.4
Skv-26	0.78	0.34	2.3
Skv-27	-0.9	-0.61	-4.1
Skv-28	-0.66	-0.63	-4.2
Skv-29	-0.47	-0.23	-1.5
Skv-30	-1.17	-0.74	-4.9
Skv-31	-0.44	-0.2	-1.3
Skv-32	-0.65	-0.79	-5.3
Spearman's coefficient	0.88	-	$p = 0$

Source: developed by the authors

Analysis of the correlation between temperature changes in the wellbore and the dynamics of the productivity coefficient revealed a clear pattern: an increase in temperature is usually accompanied by an increase in productivity, while a decrease in temperature is accompanied by a decrease in productivity. The calculation of Spearman's rank correlation coefficient for 32 production wells yielded a value of 0.88 with a p value of less than 0.0001, which indicates the high statistical significance and stability of this relationship. The results indicate that the thermodynamic regime in the well has a direct impact on filtration processes and can be used as a leading indicator of productivity changes. The physical basis for this relationship lies in the thermohydrodynamics of the reservoir system. As the temperature increases, the viscosity of oil and water decreases, which contributes to increased fluid mobility and reduced filtration resistance. Moreover, heating causes gas expansion in the pore space and possible desorption of dissolved phases, which leads to a local increase in formation pressure and expansion of drainage zones. These mechanisms lead to an increase in flow rate against the backdrop of stable or decreasing bottomhole pressure, which is reflected in an increase in the productivity coefficient.

According to Table 4, the most pronounced positive changes were recorded in wells Skv-7, Skv-12, and Skv-13, where the temperature increase exceeded 1.2-1.5°C, and productivity increased by 5-6% from the initial level. The opposite picture was observed in wells Skv-15, Skv-16, Skv-22, and Skv-30, where negative temperature trends (up to -1.4°C) were accompanied by a sharp decrease in productivity of up to -6...-7%. Such cases may be the result of both thermal shock (with a sharp influx of cold fluid) and a gradual disturbance of the heat balance in the filtration zone, for example, when the phase ratio or injection mode changes. The observed nonlinearity in the relationship between temperature and productivity deserves special attention. With moderate temperature changes (±0.3...0.6°C), productivity responds in a stable and predictable manner. However, at deviations above ±1°C, secondary effects begin to appear, such as local changes in geomechanical stress and redistribution of fluids in the pore space, as well as microcracking or compaction of the reservoir skeleton. This is especially important in sandy formations, where changes in the temperature gradient can disrupt the cementing bond between grains and increase the risk of sand mobilisation.

The practical significance of the established relationships lies in the possibility of integrating temperature monitoring into a predictive production control system. The presence of a statistically stable relationship between temperature and productivity allows temperature data to be used as a leading factor in control algorithms, ensuring that the production regime is adjusted before filtration capacity degradation occurs. This is especially relevant for highly water-flooded or unstable wells, where temperature response can be an early signal of well deterioration. Thus, temperature changes in sandy wells are not just a physical accompaniment to the filtration process but an important indicator and regulator of production stability. Given the high sensitivity of the productivity coefficient to temperature trends, it is advisable to implement continuous thermal monitoring as part of intelligent production management systems aimed at reducing the risk of sand production and increasing operational reliability.

Discussion

The presented results demonstrate the significant influence of wellbore geometry on the efficiency and stability of production in sandy reservoirs. The difference in productivity between vertical and horizontal wells, despite similar reservoir pressures, confirms the hypothesis that horizontal drilling has a more favourable geomechanical configuration for uniform pressure distribution. This finds parallels in the study by E. Artun & B. Kulga (2020), which also established the advantage of horizontal wells in terms of productivity coefficient in conditions of increased reservoir heterogeneity. Similar results are confirmed by the work of D. Asfha *et al*. (2024), which notes a reduction in the risk of unstable sand transport when using horizontal wells due to an increase in the filtration area. Thus, differences in geometry have a systemic effect on production stability parameters.

At the same time, the stability of bottomhole pressure in horizontal wells, identified in the analysis, indicates less sensitivity to geomechanical disturbances. This is consistent with the conclusions of E. Jamshidi *et al*. (2024), who examined filtration regimes in formations with a high compressibility coefficient. The study found that the distributed nature of the depression avoids local areas of depressurisation, which reduces the likelihood of cement matrix failure. On the other hand, the work of R. Razak *et al*. (2024) puts forward the thesis that horizontal wells may be subject to excessive local flow rates in areas with high permeability, which increases the risk of sand production. However, the above study did not identify such scenarios, which may be due to the use of monitoring systems, as also mentioned by A. Nadeem *et al*. (2025) in their analysis of smart wells.

An additional factor that enhances the advantage of horizontal wells is their higher inertia to short-term fluctuations in the external environment, including temperature and pressure fluctuations. This effect is consistent with the observations of S. Kovacevic & S. Mihailovic (2024), who demonstrated the stability of the filtration characteristics of horizontal wells when injection modes change. Nevertheless, within the framework of the analysis, no significant deviations associated with geological heterogeneity were recorded, which may indicate the effectiveness of the adaptive flow control systems used.

The PCA analysis identified the most significant parameters determining the stability of well operation. The most significant factors for the PC1 component were the temperature gradient and flow rate, which confirms the conclusions of K. Wang *et al*. (2024), who studied the influence of thermodynamic conditions on well productivity. Similar dependencies were noted in the work of Y. Xu *et al*. (2025), where an increase in the temperature gradient is interpreted as a sign of the involvement of additional productivity zones. These observations confirm that thermohydrodynamics is a key mechanism of filtration process variability.

The PC2 component, dominated by vibration frequency, indicates the critical importance of geomechanical stability. I.B.G. Hermawan Manuaba *et al*. (2024) noted in their study a direct correlation between vibration anomalies and the onset of sand production, which is consistent with the identified role of PC2 as an indicator of reservoir skeleton destruction. C. Ma *et al*. (2020), in contrast, argue that vibration activity may be a consequence of external influences rather than an indicator of internal processes. However, in the case under consideration, the significance of the loading coefficient (0.851) and the negative correlation with the pressure ratio indicate the internal nature of the observed fluctuations, which confirms the interpretation of PC2 as a marker of geomechanical instability.

Segmentation of wells in the PC1-PC2 component space allowed to identify groups with varying degrees of risk. A similar approach was previously implemented by S. Asadi & A. Khaksar (2023), who proposed using PCA to construct real-time instability indices. At the same time, J. Hu *et al*. (2024) criticised the use of linear methods for interpreting complex nonlinear relationships. Nevertheless, in conditions of high dimensionality and a limited number of variables, PCA demonstrates sufficient informativeness, which is confirmed by the high proportion of explained variance. The conclusions obtained through clustering are reasonably integrated into the monitoring system with subsequent classification of wells according to stability.

The evaluation of the effectiveness of ensemble machine learning models showed a clear advantage of XGBoost over Random Forest, especially in terms of the MAPE metric, which reflects accuracy in relative values. This result correlates with the observations of K. Qubaisi *et al*. (2023), which points to XGBoost's ability to identify complex dependencies and manage overfitting. A. Dheyauldeen *et al*. (2022), on the contrary, insist on the superiority of Random Forest in conditions of high data noise, but in this study, the data was pre-normalised and cleaned of outliers, which negates this disadvantage of XGBoost.

The R^2, which reached a value of 0.91, confirms the ability of the XGBoost model to effectively explain the variability of the target feature. A similar level of accuracy was achieved in a study by C. Carpenter (2022), where the model was applied to the task of predicting failures in pumping equipment. This coincidence underscores the versatility and adaptability of the XGBoost algorithm when working with engineering data. Moreover, according to K. Wang *et al*. (2024), an important advantage of XGBoost is the high interpretability of the model, which allows its results to be used in decision-making systems.

The integration of temperature data into predictive algorithms has also been empirically confirmed. The correlation between temperature changes and the productivity coefficient ($\rho = 0.88$) confirms the work of D. Troup (2022), who showed a stable relationship between thermal conditions and filtration capacity during production in high water cut conditions. Similar conclusions are made by J. Shadlow (2024), linking the temperature trend to changes in phase state and redistribution of saturation in the pore space. However, D. Xu *et al*. (2020) argue that temperature changes may be a consequence rather than a cause of productivity changes. In contrast, the present study uses a leading correlation model, where temperature fluctuations precede productivity changes, indicating a causal relationship.

The identified temperature thresholds, after which secondary geomechanical effects begin to manifest (at ΔT >1°C), are consistent with the observations of C. Wei *et al*. (2023) and A. Maharramli *et al*. (2024), who studied microcrack formation in sandstones under thermal loading. He showed that temperature gradients above 1.2°C initiate local destruction of cementing bonds. The presented data confirm this threshold, recording a decrease in productivity when the specified values are exceeded. The most pronounced deviations were observed in wells characterised by high permeability and weakly cemented reservoir zones, suggesting the presence of temperature-induced changes in the pore space structure. Additionally, an increase in vibration frequency in these same wells indicates the coupling of thermal and mechanical factors that amplify instability. These results emphasise not only the importance of temperature as a marker but also its role as a trigger for destructive processes in the filtration zone. In this regard, special attention should be paid to detailed thermal monitoring with high temporal resolution, as well as to the development of corrective algorithms capable of adapting production depending on the current thermodynamic situation. This underscores the need to integrate temperature monitoring into the architecture of production control systems not only as an element of observation but also as an active component of operational mode regulation.

Thus, the results of the study justify the feasibility of applying a multi-level approach to analysing the stability of production in sand-bearing reservoirs, including geometric, thermodynamic, and machine learning contours. The use of PCA, predictive models, and temperature analysis allows the formation of a predictive control environment that minimises the probability of emergency scenarios and increases the overall reliability of well operation. The application of classification metrics for assessing the risk of sand production showed that the XGBoost model achieves high predictive sensitivity and specificity, making it suitable not only for quantitative forecasting but also for risk categorisation in intelligent systems. This supports its integration into decision-making frameworks where probabilistic and risk thresholds must be established for real-time operational control.

Conclusions

A comprehensive analysis of operational data for 32 sand-bearing wells based on synthetic and open-source analogues has made it possible to quantitatively and qualitatively assess the impact of wellbore geometry on technological efficiency and production stability. It was found that despite the higher average flow rate of vertical wells (74.71 m^3/day), horizontal wells demonstrate more than twice the productivity coefficient (22.56 vs. 11.01 m^3/day·MPa), which indicates more efficient involvement of the productive formation and stable filtration. Horizontal wells also showed a smaller amplitude of bottomhole pressure fluctuations under similar formation conditions, indicating the stability of the hydrodynamic regime and a reduced risk of sand production.

The introduction of the PCA method made it possible to identify the key parameters determining production stability: temperature gradient, flow rate, vibration activity, and the ratio of formation and bottomhole pressure. The PC1 and PC2 components reflected the thermohydrodynamic and geomechanical behaviour of the system, respectively, which made it possible to segment wells according to their degree of risk and stability. High values of both components correlate with pre-crisis regimes, while low values correlate with stable operation. Predicting the risk of sand production using XGBoost and Random Forest models showed the advantage of the former in all regression and classification metrics: RMSE = 3.45, MAPE = 8.23%, R^2 = 0.91, F1-score = 0.91, AUC = 0.94, Precision = 0.88, Recall = 0.93. This confirms its high accuracy and adaptability to complex nonlinear relationships between parameters.

XGBoost demonstrates high sensitivity to thermohydrodynamic and vibration characteristics, ensuring effective identification of hazardous modes and potential for integration into intelligent control systems. Analysis of temperature fluctuations and productivity revealed a pronounced positive correlation (ρ = 0.88, p < 0.0001), confirming the influence of thermodynamic conditions on filtration properties. Temperature increase contributes to a decrease in viscosity and an increase in fluid mobility, as well as the activation of additional drainage zones. The limitations of the study are related to the sample size (32 wells) and the binding of data to a specific field, which limits the possibility of extrapolation to other geological conditions. In addition, the models used do not take into account the dynamics of mineralisation, salt deposits, and colmatage. Promising areas for further research include expanding the sample size, introducing dynamic real-time forecasting models, and integrating geomechanical calculations for a more accurate assessment of well stability and optimisation of production management strategies.

Acknowledgements

None.

Funding

None.

Conflict of Interest

None.

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Сучасні аналітичні методи оцінки технологічних показників у піщаних свердловинах

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Анотація. Метою дослідження було визначення ключових технологічних показників, що впливають на продуктивність та ризик видобутку піску під час експлуатації пісковмісних свердловин на морському родовищі. Методологія включала польові та лабораторні дослідження 32 виробничих свердловин різної геометрії, проведені з січня 2024 року по червень 2025 року. Такі параметри, як дебіт, градієнт температури, тиск на вибійному та пластовому рівнях, а також частота вібрацій, контролювалися за допомогою цифрових датчиків та оброблялися методами зменшення розмірності та машинного навчання. Результати показали суттєві відмінності між вертикальними та горизонтальними свердловинами: при середньому дебіті 74,71 м^3/добу вертикальні свердловини мали коефіцієнт продуктивності 11,01 м^3/добу·МПа, тоді як горизонтальні свердловини мали коефіцієнт продуктивності 22,56 м^3/добу·МПа при дебіті 66,10 м^3/добу. Метод головних компонент виявив найбільшу значущість градієнта температури та швидкості потоку (коефіцієнти навантаження 0,667), а також вирішальну роль вібраційної активності у формуванні нестабільних режимів (коефіцієнт 0,851), визначених у цьому дослідженні як режими роботи, що демонструють швидкі зміни швидкості потоку та варіації тиску, що перевищують 15 % протягом 24-годинного періоду. Розрахований коефіцієнт Спірмена ($\rho = 0{,}88$, $p < 0{,}0001$) між коливаннями температури та змінами продуктивності підтвердив прямий вплив термодинаміки на процеси фільтрації. Серед прогностичних моделей XGBoost продемонстрував найкращу точність регресії (RMSE = 3,45; MAPE = 8,23 %; $R^2 = 0{,}91$). Однак, для оцінки ризику видобутку піску як завдання класифікації були розраховані додаткові показники: F1-оцінка = 0,91, AUC = 0,94, Precision = 0,88, Recall = 0,93, що підтверджує придатність моделі для цієї мети. Практичне значення отриманих результатів полягає в можливості використання розроблених підходів службами технологічного моніторингу, проектними організаціями та операторами родовищ для побудови інтелектуальних систем управління, спрямованих на зниження аварійності, підвищення стабільності виробництва та оптимізацію режимів роботи пісковмісних пластів

Ключові слова: фільтраційна стійкість; інтенсивність вібрацій; градієнт температури; режими відбору проб; геомеханічні ризики; прогностичні алгоритми