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A data-driven approach for minimising production deferrals in sand-prone oil wells

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Abstract. The aim of the study was to develop an analytical approach to minimising lost production in sand-prone oil wells based on operational data from the Caspian region, including facilities in Azerbaijan. The research methodology was based on an empirical analysis of monthly production observations from 48 producing wells for the period 2024-2025 and included a comparison of stable and unstable production intervals, a quantitative assessment of the contribution of operational factors to the formation of lost production, predictive modelling of unstable states and production losses, as well as an engineering verification of the identified patterns under real operational constraints. It was established that the transition to an unstable operational state was accompanied by a 23.5% decrease in oil flow rate, a 47.9% increase in water cut, a 69.8% increase in pressure drop across the filter elements, a 3.8-fold increase in downtime duration, and a 154.5% increase in the frequency of operational interventions. A statistical comparison showed that the most pronounced differences between stable and unstable intervals were associated with the rate of decline in flow rate, an increase in water cut, the cumulative duration of downtime over a six-month window, and a reduction in the proportion of stable production without signs of sand production. Regression analysis revealed that the greatest contribution to the change in lost production was made by the pressure drop across the filter elements, the proportion of stable operation, cumulative downtime and the frequency of interventions, whilst in the predictive modelling block, the XGBoost model demonstrated the best results, with an average absolute error of 2.18 m^3 per month and a coefficient of determination of 0.79. The practical significance of the results lies in their potential application in production monitoring and operational management systems for sand-prone wells, enabling the early detection of unstable conditions, the justification of operational interventions, and the adjustment of production rates to minimise lost production

Keywords: operational instability; filtration resistance; accumulation of downtime; frequency of operational interventions; proportion of stable operation; predictive modelling; production losses

Introduction

Sand production in oil wells is regarded as one of the factors reducing operational stability and production efficiency, since the transport of solid particles is accompanied by a disruption of the operating conditions in the bottomhole zone, an increase in the load on well equipment, a rise in the number of operational interventions, and an increase in downtime duration. For weakly cemented reservoirs, this relationship is systemic in nature, as the transition to an unstable operating regime is caused by the combined action of geomechanical, hydrodynamic and operational factors. Consequently, the analytical focus has shifted from describing individual manifestations of sand washout to developing integrated solutions based on a combination of control methods, operational monitoring and predictive modelling. Scientific interest in the problem of sand blowouts has gradually shifted from describing individual mechanisms of sand blowouts to developing integrated approaches based on a combination of methods for preventing sand blowouts, operational monitoring and predictive analytics (Deryaev, 2024a).

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In a review paper by D.T. Asfha *et al*. (2024), the mechanisms of sand migration, approaches to its prediction, and the potential applications of fibre-optic technologies and machine learning methods for monitoring well conditions are systematised. It is shown that the development of sand control risk management systems is linked not only to the improvement of technical monitoring tools, but also to the expanded use of real-time data and intelligent analysis methods. A similar aspect of sand control management in the context of selecting technological solutions is considered in the work by M. Muhammad and A.A. Rasol (2025). The authors' analysis showed that the management of sand production is complicated not by a lack of available technologies, but by the need to select them judiciously, taking into account operating conditions, well operating modes and economic constraints. The study by H. Wu *et al*. (2025) summarises current understanding of the mechanisms of sand production, risk factors, forecasting methods and directions for further development in this field. The authors concluded that sand production should be regarded as a dynamic, multi-factor process, the analysis of which requires a combination of mechanistic models and predictive methods.

The chemical approach to controlling sand migration is presented in the publication by I. Karimov (2026a), which examines the transition from polymer solutions to nanomaterials in chemical sand stabilisation technologies. It is shown that the stability of such treatment should be assessed taking into account the preservation of the collector's filtration properties, which allows it to be considered in the context of long-term operational efficiency, rather than merely a short-term reduction in sand washout. A separate area of research concerns the evaluation of the performance of filtration systems. In the work by S. Liu (2024), a method for analysing the efficiency of slotted filters is proposed, according to which their operational characteristics depend not only on design parameters but also on operating conditions that determine the pressure drop, the degree of clogging, and the stability of solid particle retention.

The diagnostic aspect is addressed in the field study by D.T. Asfha *et al*. (2026), which demonstrates the capabilities of vertical seismic profiling technology using distributed acoustic sensing for the real-time detection of sand migration in an offshore well. It is shown that sand flow signatures can be used for the rapid detection of adverse changes in operating conditions, confirming the importance of continuous monitoring in production management systems. In the work by M.H. Shabdirova *et al*. (2023), machine learning methods are applied to predict non-stationary sand intrusions using the Karazhanbas field as an example. It has been shown that non-linear relationships between operational parameters and the development of sand production can be identified analytically; however, their correct interpretation requires consideration of the specific production context and the structure of the source data. In a review paper by B.A. Suleimanov *et al*. (2024) systematise mechanical technologies for preventing sand production in oil and gas wells. The authors demonstrate that the performance of filters and gravel packs is determined not only by their design characteristics, but also by their suitability to the selection conditions, flow capacity requirements, and the actual operating regime of the well. Early signs of instability in the bottomhole zone were examined by I. Karimov (2026b) based on an analysis of wellhead pressure and throttling parameters. A conclusion was drawn regarding the diagnostic significance of standard field indicators, which expands the possibilities for analytical forecasting by identifying adverse changes in operating conditions without the mandatory use of specialised measurements. The relationship between sand control and production efficiency is examined in the study by S. Ismayilov and Z. Mirzayev (2025), where innovative approaches to the operation of wells with sand production are analysed through a system of operational indicators. It is shown that their effectiveness is determined not only by a reduction in sand carryover, but also by their impact on flow rate stability, well operating conditions and the overall set of operational parameters.

Thus, a review of the literature shows that studies of sand production in oil wells cover the mechanisms of sand carryover, risk factors for unstable operation, mechanical and chemical control methods, monitoring tools, as well as analytical and predictive approaches to identifying adverse operating conditions. At the same time, there is a limited number of studies in which well operational data are simultaneously used to quantitatively assess lost production, predict the transition to an unstable operating regime, and justify technological solutions for reducing production losses. In this regard, the aim of the study was to substantiate an analytical approach to reducing lost production in sand-prone oil wells in the Caspian region, including Azerbaijan. In accordance with the stated objective, the study was aimed at addressing the following tasks: identifying key operational predictors of an unstable operational state of a well, assessing factors influencing the volume of lost production, and determining analytically sound guidelines for the engineering interpretation of threshold states and the selection of possible technological solutions.

Materials and Methods

The study was carried out between 2024 and 2025 as an empirical analysis of operational data, involving the development of an analytical approach designed to reduce production losses in sand-prone oil wells. The methodological framework was developed taking into account the conditions for the development of weakly cemented reservoirs in the Caspian region, including sites in Azerbaijan. This research framework is consistent with published engineering literature on the Azeri, Chirag and Azeri-Chirag-Gunashli fields, where sand production is considered a significant factor in reducing production efficiency and the operational reliability of equipment (BP, 2002; Susilo *et al*., 2013; SLB, 2024).

The empirical basis of the study was formed using production monitoring data from 48 production wells and comprised a dataset of 1,728 monthly observations. The sample included wells with a continuous or quasi-continuous series of observations spanning at least 36 months. To ensure comparability between sites, a single analytical horizon of 36 months was used. This approach enabled the data on flow rates, bottomhole and wellhead pressures, water cut, signs of sand production, operational interventions and downtime duration to be presented in a comparable format. An integrated analytical profile was formed based on the initial dataset, combining production, hydrodynamic and operational indicators, as well as information on the dates of interventions and the duration of downtime. Operational interventions were identified using retrospective production data containing information on the occurrence of shutdowns, the nature of the operations performed, the duration of downtime, and the subsequent resumption of well operations. The study considered unscheduled operations aimed at restoring or stabilising well performance as operational interventions, including the cleaning of filter elements, the removal of sand and mechanical deposits, the restoration of bottomhole zone permeability, and flushing operations. In engineering practice, such interventions are regarded as measures for the maintenance, repair and restoration of well performance, including in conditions where sand control systems are malfunctioning (Schlumberger, 2015; Tang *et al.*, 2022).

The frequency of operational interventions was defined as the number of relevant events per 12 months of observation for each well. Objects with significant data gaps, disrupted temporal consistency, and values lacking operationally interpretable content were excluded from further processing. Intervals within which changes in operating mode could not be reliably correlated with the actual condition of the well were also excluded. Data preparation involved cleaning the dataset, standardising time intervals, and converting the indicators into a uniform analytical format. Missing values were imputed only where this did not conflict with the operational logic of the process. For short gaps in the time series, local linear interpolation was applied, as with a short gap and no signs of technological intervention, this approach allowed the continuity of the series to be maintained without significantly distorting the overall dynamics of the operational indicators. This procedure was used only on locally stable sections of the observations. For parameters exhibiting step-like changes, the nearest valid value was carried over, provided that a physically permissible operating regime was maintained. Anomalous values were interpreted taking into account the operational context, as sharp deviations could be associated with both recording errors and actual manifestations of unstable well operation. Derivative indicators were calculated based on the initial operational parameters to characterise the well's transition to an unstable operational state. The rate of decline in flow rate was defined as the relative change in average flow rate between the current and previous three-month observation windows (1):

$$R_q = (\bar{Q}_t - \bar{Q}_{t-1})/\bar{Q}_{t-1}, \qquad (1)$$

where $\bar{Q}_t$ – average flow rate in the current three-month period, m³/day; $\bar{Q}_{t-1}$ – average flow rate in the preceding three-month window, m³/day. In addition, the rate of change in water saturation (ΔWC), the absolute and relative changes in bottomhole and wellhead pressures ($\Delta P\text{₦}_h$ and $\Delta P w_h$), the cumulative duration of downtime within a six-month window (DT_{6m}), and the frequency of operational interventions over a 12-month period were calculated. The choice of a three-month window for the flow rate and water cut indicators was determined by the need to smooth out short-term operational fluctuations whilst maintaining sensitivity to adverse changes in operating conditions. A six-month window was used to assess the cumulative effect of downtime and recurring interruptions to the well's continuous operation. Calculations were performed using a moving average method with a monthly step. The average flow rate in the current three-month window was defined as the arithmetic mean of the values for months t, $t-1$ and $t-2$, and the average flow rate in the preceding window as the arithmetic mean of the values for months $t-1$, $t-2$ and $t-3$. The cumulative duration of downtime was calculated as the sum of the duration of downtime over six consecutive months, including the current month of observation (2):

$$DT_{6m} = \Sigma\, DT_{t-1},\ i = 0 \ldots 5, \qquad (2)$$

where DT_{t-1} is the duration of downtime in the relevant month, in days. This approach made it possible to identify a consistent trend of deterioration in operating conditions, rather than isolated technical deviations. An unstable operating condition was identified based on a combination of operational indicators, including signs of solid particle carryover, an increase in pressure drop across the filter elements of at least 15% compared with the preceding stable interval, a reduction in oil flow rate of at least 10% in the absence of external constraints on the production regime and unscheduled operational interventions (Abduljabbar *et al.*, 2024). Their selection was based on the field interpretability of the indicators, a preliminary comparison of stable and unstable observation intervals, and an engineering verification of the physical plausibility of the identified deviations within the framework of scenario analysis. For analytical processing, such states were coded in two ways: as a binary event of transition to an unstable operational state and as a quantitative indicator of the severity of production losses, expressed as the volume of lost production. The *SFR* indicator was calculated as the ratio of the duration of stable operation intervals without recorded signs of sanding to the total duration of the period under analysis (3):

$$SFR = T_{sta\beta le}/T_{total}, \qquad (3)$$

where $T_{sta\beta le}$ – total duration of stable operation without signs of sand transport; T_{total} – total duration of the analysed period. This indicator was used as an integral measure of the well's operational stability. The main target variable was the volume of oil not produced, defined as the difference between the expected production, calculated based on the well's baseline steady-state flow rate, and the actual production over the analysed interval (4):

$$L_o = (Q_{base} - Q_{fact}) \times t, \tag{4}$$

where L_o – volume of oil not produced, m^3; Q_{base} – base oil production rate, determined by the average production rate during the preceding steady-state period of operation for a specific well, m^3/day; Q_{fact} – actual oil production rate in the interval under analysis, m^3/day; t – duration of the analysed interval, days.

In addition, the probability of a well entering an unstable operational state, accompanied by sand production, an increase in the number of interventions and a rise in downtime, was assessed. The analytical procedure comprised several stages. In the first stage, a descriptive analysis was performed to identify stable relationships between operational parameters, signs of sand production, reduced production, and downtime duration. In the second stage, regression models were applied to quantitatively assess the contribution of individual factors to production losses. To this end, multiple linear regression, ridge regression and models with selection of the most significant predictors were used. This made it possible to assess the influence of pressure, flow rate, water cut, frequency of interventions and sand production indicators on the amount of lost production. In the third stage, machine learning methods were used to solve three analytical problems: classification of unstable operational states, forecasting of lost production volume, and assessment of the significance of input variables. Logistic regression was applied for the binary classification of well conditions. Random forest and gradient boosting were used to identify non-linear relationships and rank factors by degree of influence. To improve the accuracy of the forecast of lost production, the XGBoost algorithm was additionally applied. The data were split into training and test sets in an 80:20 ratio, whilst preserving the group structure of observations by well and time interval. This prevented the transfer of information between samples and minimised the risk of data leakage. The robustness of the results was further verified using a five-fold cross-validation method with grouping by well.

Statistical analysis of the data was carried out on a case-by-case basis, taking into account the distribution type of the variables under analysis and the research objective. In the first stage, the normality of the distribution was tested using the Shapiro-Wilk test. Statistical comparison of operational indicators between groups of wells with stable and unstable operating modes was carried out taking into account the type of data distribution. For a normal distribution, Student's t-test was applied; for deviations from normality, the Mann-Whitney test was used. The Wilcoxon criterion was used to analyse related states of the same well, including periods before and after technological intervention or before and after the transition to a regime with signs of sand production. The level of statistical significance was set at $p < 0.05$. Classical statistical methods were used to test inter-group and intra-group differences, whilst the machine learning module was focused on solving predictive and ranking tasks. The quality of the predictive models was assessed by the mean absolute error, root mean square error and coefficient of determination in regression tasks, as well as by classification accuracy, completeness, positive prediction accuracy and F1-score in classification tasks. When interpreting the results, priority was given to the completeness of identifying unstable states, as missing such episodes was associated with higher production losses and a risk of equipment damage. Data processing and model building were performed in the Python environment using Jupyter Notebook (n.d.). The PIPESIM (n.d.) hydraulic simulator was additionally used for engineering verification of the results and scenario analysis. This was used to assess the relationship between production modes, well completion parameters and changes in key operational indicators, including additional filtration resistance, productivity coefficient, pressure drop and the stability of filtration systems. The practical applicability of the proposed approach was further assessed taking into account the regulatory constraints of American Petroleum Institute (1991) and ISO 17824:2009 (2009). The scenario analysis considered options for varying formation pressure, the use of sand control systems, and their combination with other operational interventions. The results of the PIPESIM simulation were used for engineering verification of the calculations, interpretation of the threshold values established by statistical and predictive models, and to confirm the physical plausibility of the identified predictors of an unstable operating state.

Results

Initial differences between stable and unstable operating intervals

A comparison of stable and unstable production intervals in a dataset comprising 48 production wells and 1,728 monthly observations showed that the transition to an unstable production state was accompanied not by an isolated deviation in a single operational parameter, but by a coordinated change in the key parameters of well performance. Even at the initial descriptive level, unstable intervals were characterised by a simultaneous decrease in oil production, an increase in water cut, a rise in pressure drop across the filter elements, longer downtime periods, and a higher frequency of operational interventions. This pattern of changes was accompanied by a simultaneous deterioration in production, hydrodynamic and operational characteristics and was consistent with the general engineering logic described for sand-prone development conditions at the Azeri-Chirag-Gunashli fields (BP, 2002; Susilo *et al.*, 2013; SLB, 2024).

The most pronounced differences between stable and unstable intervals were identified in terms of oil flow rate, pressure drop across the filter elements, duration of downtime and volume of lost production. In stable intervals, the flow rate remained at a higher level, whereas in unstable conditions it decreased against a background of increasing water cut and local flow resistance. At the same time, downtime duration and the frequency of operational interventions increased, accompanied by changes not only in filtration and hydrodynamic conditions but also in the overall operational load on the production system. Consequently, production losses in such intervals became recurrent and accumulated over time. The decline in productivity, the increase in internal resistance and the rise in the number of operational disruptions manifested themselves as interrelated processes (Deryaev, 2024b). To systematise the primary differences between stable and unstable operational intervals, Table 1 presents summary characteristics of the main technological indicators.

Table 1. Descriptive characteristics of stable and unstable operating intervals

Indicator	Stable intervals	Unstable intervals	Change
Oil flow rate, m^3/day	96.8±10.9	74.1±12.6	-23.5%
Bottomhole pressure, MPa	19.4±2.3	17.2±2.7	-11.3%
Wellhead pressure, MPa	6.3±0.9	7.5±1	+19%
Water saturation, %	26.9±8.7	39.8±10.6	+47.9%
Pressure drop across the filter elements ΔP_f, MPa	0.96±0.21	1.63±0.29	+69.8%
Downtime duration, days/month	1.4±0.9	5.4±1.7	+285.7%
Frequency of technical interventions, cases/year	1.1±0.4	2.8±0.7	+154.5%
Unrealised production, m^3/month	2.1±1.3	14.7±4.8	7 times higher

Source: compiled by the author based on the results of processing the operational dataset and computational procedures in the Python/Jupyter environment

As can be seen from Table 1, the differences between stable and unstable intervals were not localised but rather consistent in nature, and encompassed production, hydrodynamic and operational parameters simultaneously. In unstable intervals, the oil flow rate decreased from 96.8 to 74.1 m^3/day, i.e., by 23.5%, whilst water cut increased from 26.9 to 39.8%, indicating a deterioration in the inflow structure and a reduction in production recovery efficiency. At the same time, the pressure drop across the filter elements ΔP_f increased from 0.96 to 1.63 MPa, or by 69.8%, reflecting an increase in local flow resistance and a deterioration in filtration conditions in the bottomhole zone. The change in pressures throughout the system was also consistent: bottomhole pressure decreased by 11.3%, whilst wellhead pressure, conversely, increased by 19%, which further indicated a shift in the well's operating regime as operating conditions deteriorated. The most pronounced shifts were related to the operational component: downtime duration increased from 1.4 to 5.4 days/month, i.e., by more than 3.8 times, whilst the frequency of operational interventions rose from 1.1 to 2.8 instances per year, or by 154.5%. As a result, lost production in unstable intervals reached 14.7 m^3/month compared to 2.1 m^3/month in stable intervals, i.e., it was 7 times higher. This combination of changes indicated that the transition to an unstable operating state was accompanied not by a separate deterioration of a single indicator, but by a simultaneous decline in productivity, an increase in hydrodynamic resistance, a reduction in operational continuity, and an accumulation of production losses. This interpretation is consistent with the general engineering view of the degradation of a well's operating regime as a process accompanied by the need for more frequent restorative and stabilising measures, particularly when the functioning of sand-control systems deteriorates (Schlumberger, 2015; Tang *et al.*, 2022).

Thus, an initial comparison of stable and unstable operating intervals revealed that the development of an unstable state in sand-prone wells manifested itself as a complex of interrelated changes affecting flow rate, water cut, pressure parameters, downtime duration, intervention frequency and lost production. Even at a descriptive level, this indicated that operational instability manifested as a systemic deterioration in well performance, rather than as an isolated deviation in a single operational parameter. The differences identified formed the basis for further analysis of derived indicators, statistical signs of the transition to an unstable state, and a quantitative assessment of factors associated with an increase in production losses.

Derivative indicators and statistical signs of the transition to an unstable operational state

A comparison of the derived indicators revealed that the transition to an unstable operational state was accompanied not only by changes in the initial operational parameters, but also by changes in the indicators reflecting the dynamics of the operating regime, the accumulation of operational irregularities, and a reduction in the proportion of stable well operation. This approach to interpreting an unstable state as a set of operational markers corresponds to the accepted scheme for its identification (Abduljabbar *et al.*, 2024). Differences between stable and unstable intervals were identified based on the rate of decline in flow rate, the rate of increase in water cut, changes in bottomhole and wellhead pressure, the accumulated duration of downtime within a six-month window, the annual frequency of interventions, and the *SFR* indicator. This pattern of differences was accompanied by the accumulation of interrelated signs of operational deterioration, including a decline in productivity, changes in hydrodynamic conditions, and a reduction in the duration of stable operation. In unstable intervals, the negative flow rate trend was accompanied by increased water cut and simultaneous pressure changes throughout the production system. The increase in DT_{6m} and the annual intervention frequency indicated that the change in operating regime was accompanied not only by filtration and hydrodynamic deviations, but also by changes in operational parameters. The *SFR* indicator decreased during such intervals, reflecting a reduction in the proportion of time during which the well operated without signs of sand production and associated disruptions. Taken together, the derived indicators reflected not isolated deviations, but a transition process from a steady state to a regime in which production losses recurred over time. For a quantitative comparison of the indicators calculated on the basis of the initial operational data, including the derived indicators determined by formulas (1)-(4), the results of the statistical analysis are presented in Table 2.

Table 2. Results of the statistical comparison of derived indicators and associated signs of deterioration in operating conditions

Indicator	Stable Intervals	Non-Robust Intervals	p-value
R_q	-0.03±0.02	-0.11±0.04	<0.001
ΔWC, %	+1.8±1.1	+6.9±2.4	<0.001
$\Delta P_{\beta h}$, MPa	-0.4±0.3	-1.7±0.6	<0.001
ΔP_{wh}, MPa	+0.2±0.2	+0.9±0.4	<0.001
DT_{6m}, days	6.1±2.8	18.7±5.3	<0.001
Frequency of interventions, cases/year	1.1±0.4	2.8±0.7	<0.001
SFR	0.84±0.07	0.46±0.09	<0.001
Shortfall in production, m^3/month	2.1±1.3	14.7±4.8	<0.001

Note: to compare indicators between stable and unstable intervals, the Student's t-test or the Mann-Whitney test was used, depending on the nature of the data distribution as determined by the Shapiro-Wilk test
Source: compiled by the author based on the results of statistical analysis of operational data using Python/Jupyter

According to the data in Table 2, the transition to an unstable operational state was most clearly evident in the R_q, ΔWC, DT_{6m} and *SFR* indicators. In unstable intervals, the value of R_q varied from -0.03±0.02 to -0.11±0.04, reflecting a more pronounced decrease in discharge compared to stable states. At the same time, ΔWC increased from +1.8±1.1 to +6.9±2.4%, accompanied by a more pronounced adverse trend in water availability. The cumulative duration of downtime in the six-month DT_{6m} window increased from 6.1±2.8 to 18.7±5.3 days, i.e., more than threefold. Against this background, the *SFR* decreased from 0.84±0.07 to 0.46±0.09, reflecting a reduction in the proportion of operating time without signs of sanding and associated disruptions. All differences remained statistically significant at the $p<0.001$ level. This combination of changes indicated that the transition to an unstable state was accompanied not by a single isolated shift, but by a simultaneous change in several interrelated characteristics of the operating regime. A more pronounced decrease in flow rate was accompanied by an increase in waterlogging, an accumulation of downtime, and a reduction in the duration of stable operation. Consequently, differences between stable and unstable intervals were recorded not only in terms of the absolute values of the parameters, but also in terms of the direction of their change over time. In this form, the derived indicators were used to identify that part of the operational dynamics which was accompanied by a further increase in lost production and characterised the development of an unstable operational state.

Regression analysis of factors influencing lost production

A regression analysis of the factors influencing lost production revealed that changes in production volume in sand-prone wells were accompanied by the combined effect of several operational parameters, reflecting changes in filtration conditions, an increase in hydrodynamic resistance, and changes in the stability of the operating regime. The strongest correlation with the magnitude of production losses was found for the pressure drop across the filter elements, the frequency of operational interventions, the cumulative duration of downtime, and the *SFR* index. The coefficients of the regression models showed that the volume of lost production varied both as hydrodynamic conditions deteriorated and as the proportion of time spent in stable operation decreased. This pattern of results indicated a link between production losses and the well's transition to a regime in which operational disruptions recurred over time. The direction of influence of individual factors remained consistent in both the multiple linear regression model and the regularised model. This indicated the stability of the identified relationships between operational indicators and the volume of lost production. A decrease in flow rate, an increase in ΔP_f, an increase in DT_{6m} and an increase in the frequency of interventions were considered, within the framework of regression analysis, as interrelated changes in the operating regime. With this combination of parameters, an increase in deviations was accompanied by an increase in accumulated production losses and a change in the well's operating conditions. For a visual comparison of the relative contribution of key predictors within the regression approach, their effects are presented in Figure 1. As shown in Figure 1, a graphical comparison of the coefficients revealed a similar pattern of how the predictors influenced the volume of lost production in both regression models. The coefficients with the largest absolute values were ΔP_f, *SFR*, DT_{6m} and the frequency of technical interventions, indicating a link between an increase in filtration resistance, a reduction in the proportion of stable operation, the accumulation of downtime and an increase in the number of operational disruptions, and the occurrence of production losses. In the multiple linear regression model, the coefficient for ΔP_f was 0.34, for *SFR* -0.32, for DT_{6m} 0.29, and for the frequency of interventions 0.25. In the ridge regression, the same direction of influence was maintained, along with coefficients of similar magnitude: 0.31 for ΔP_f, -0.29 for *SFR*, 0.27 for DT_{6m} and 0.23 for the frequency of interventions. This indicated that an increase in the pressure drop across the filter elements, the accumulated downtime and the number of operational interventions was accompanied by a rise in lost production, whereas an increase in the proportion of time spent in stable operation was accompanied by a decrease in lost production.

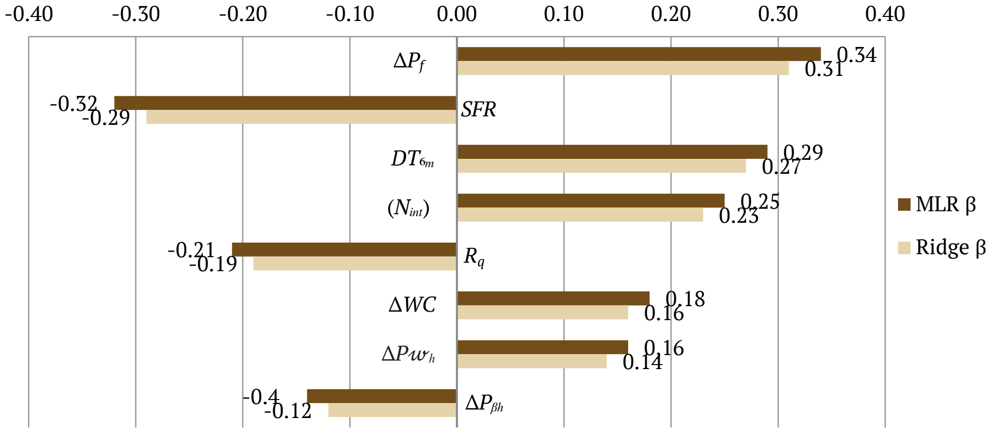

Figure 1. Comparison of β coefficients in regression models of lost production

Source: compiled by the author based on the results of visualising the β coefficients of regression models in the Python/Jupyter environment

The differences between the models did not alter the overall structure of the relationships, and the similar values of the coefficients indicated the comparability of the estimates across different regression analysis methods. Derived indicators of operational mode changes were also associated with production losses. The coefficient for R_q was -0.21 in the linear model and -0.19 in the peak model, reflecting the relationship between a decrease in flow rate and an increase in lost production. For ΔWC, the coefficients were 0.18 and 0.16 respectively, indicating a link between increased water cut and increased production losses. Pressure parameters also maintained a unidirectional relationship with the dependent variable: for $\Delta P_{\beta h}$, the coefficients were -0.14 and -0.12, and for $\Delta P w_h$, 0.16 and 0.14. All the coefficients mentioned remained statistically significant, as the p-values ranged from <0.001 to 0.011. The explanatory power of the models was similar: R^2 was 0.71 for multiple linear regression and 0.69 for ridge regression. The results obtained indicated a link between shortfall in production and the combined change in several parameters characterising filtration, hydrodynamic and operational conditions. Thus, the regression analysis showed that the increase in lost production in sand-prone wells was associated not with a single operational deviation, but with a simultaneous change in several operating parameters. The coefficients with the largest absolute values were obtained for ΔP_f, *SFR*, DT_{6m} and the frequency of operational interventions, whilst the indicators of flow rate dynamics, water cut and pressure complemented the overall structure of the identified relationships. The consistency in the direction of the effects and the similar values of the coefficients in both models indicated the comparability of the regression analysis results. This allowed the findings to be used for subsequent comparison with machine learning results and for ranking features according to their predictive significance.

Machine learning results for the classification of unstable states, the prediction of lost production, and the ranking of features

The machine learning results showed that the transition to an unstable operational state and changes in the volume of lost production were reflected not only in statistical and regression relationships, but also in predictive patterns within the operational data. A comparison of algorithms revealed differences between models in terms of the completeness of unstable interval detection and the accuracy of production loss forecasting. Ensemble algorithms proved to be the most sensitive to combinations of features associated with a deterioration in operating conditions. Among these, the most significant were a decrease in flow rate, an increase in ΔP_f, a decrease in *SFR*, an accumulation of DT_{6m}, and an increase in the frequency of operational interventions. This configuration of features indicated that an unstable operational state was described not by a single variable, but by a system of interrelated parameters. The results of classification and regression modelling were consistent in terms of the general logic of feature selection. Models that more accurately identified unstable intervals simultaneously demonstrated greater sensitivity to the combination of parameters previously identified in statistical and regression analysis. This indicated the stability of the feature structure across different analytical levels and confirmed that key operational mode indicators retained their significance both for classifying well states and for predicting the magnitude of production losses. To compare the predictive performance of the algorithms used, the model quality metrics are presented in Table 3.

Table 3. Comparison of the quality of machine learning models for instability classification and production shortfall prediction

Model	Task	Accuracy	Recall	Precision	F1-score	MAE	RMSE	R^2
Logistic Regression	Classification	0.84	0.81	0.79	0.80	-	-	-
Random Forest	Classification	0.89	0.87	0.85	0.86	-	-	-
Gradient Boosting	Classification	0.91	0.89	0.88	0.88	-	-	-
XGBoost	Forecast of lost revenue	-	-	-	-	2.18	3.04	0.79
Random Forest Regressor	Forecast of lost production	-	-	-	-	2.54	3.41	0.74
Gradient Boosting Regressor	Forecast of lost revenue	-	-	-	-	2.31	3.17	0.77

Note: Accuracy, Recall, Precision and F1-score were used to evaluate models for classifying unstable operational states; MAE, RMSE and R^2 were used to evaluate models for predicting lost production. The symbol "-" indicates that the metric is not applicable to the corresponding model

Source: compiled by the author based on the results of operational data processing and machine learning in the Python/Jupyter environment

As can be seen from Table 3, in the task of classifying unstable operational states, higher metric values were obtained for ensemble algorithms. For Gradient Boosting, the accuracy was 0.91, recall 0.89, precision 0.88, and F1-score 0.88. For Random Forest, the corresponding values were 0.89, 0.87, 0.85 and 0.86, and for Logistic Regression – 0.84, 0.81, 0.79 and 0.80. These differences indicated that ensemble models distinguished between stable and unstable intervals more accurately. The higher Recall value for Gradient Boosting indicated a smaller number of undetected unstable intervals. The differences between logistic regression and ensemble algorithms also showed that the classification of operational states was related not only to a linear combination of features, but also to their more complex structure.

In the task of forecasting shortfall in production, the lowest error values and the highest coefficient of determination were obtained for XGBoost: MAE was 2.18 m³/month, RMSE was 3.04 m³/month, and R^2 was 0.79. For the Gradient Boosting Regressor, the corresponding values were 2.31 m³/month, 3.17 m³/month and 0.77, and for the Random Forest Regressor – 2.54 m³/month, 3.41 m³/month and 0.74. These results showed that XGBoost provided a lower prediction error and a higher proportion of explained variation in lost production within the dataset under consideration. The differences between the models indicated that the prediction of production losses was associated with a combination of several interrelated features. The machine learning results reproduced the same pattern of relationships that had been identified in the previous stages of the analysis. The features that demonstrated statistical significance and a regression relationship with lost production in this block also determined the quality of classification and prediction. This showed that the identified system of variables was used not only to distinguish operational states, but also to predict the transition to an unstable regime and changes in the volume of production losses. For a visual comparison of the significance of features in machine learning models, the results of their ranking are presented in Figure 2.

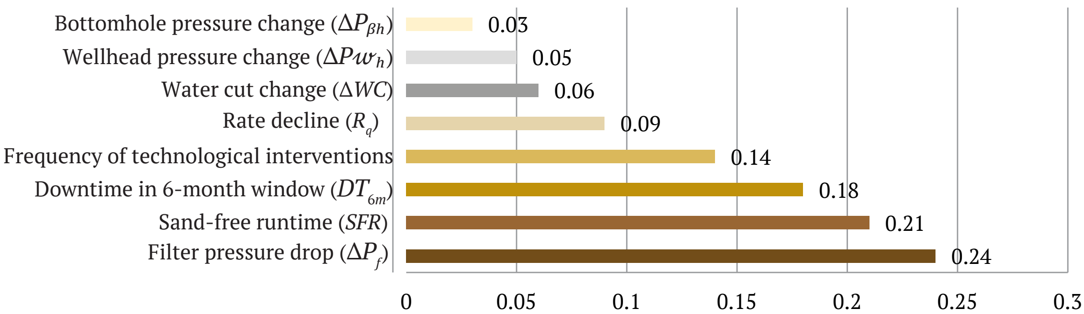

Figure 2. Ranking of feature importance in machine learning models

Source: compiled by the author based on the results of feature importance analysis and visualisation in the Python/Jupyter environment

As shown in Figure 2, the features with the highest significance in the machine learning models were ΔP_f, SFR, DT_{6m}, the frequency of process interventions and the rate of flow rate decline. Their relative significance values were 0.24 for ΔP_f, 0.21 for SFR, 0.18 for DT_{6m}, 0.14 for the frequency of operational interventions and 0.09 for R_q. These variables were associated with both the probability of a well transitioning to an unstable operational state and the magnitude of lost production. This distribution of significance indicated that the models primarily utilised features reflecting changes in local resistance, a reduction in the proportion of time spent in stable operation, and the accumulation of operational disruptions. In this respect, machine learning reproduced the same feature structure that had been identified in the statistical and regression analyses.

The significance of *SFR* and DT_{6m} was comparable to that of ΔP_f and flow rate dynamics. This showed that not only hydrodynamic deviations but also temporal characteristics of well operation, including changes in the proportion of stable operation, the accumulation of downtime, and the frequency of operational interventions, were used to identify unstable modes. Thus, production losses in sand-prone wells were associated not only with changes in the filtration state, but also with a restructuring of the operational regime. Machine learning results showed that unstable operational states and the associated increase in lost production were identified based on a combination of operational parameters. The greatest contribution to the quality of classification and forecasting was made by features reflecting changes in resistance, a decline in productivity, the accumulation of downtime, and a reduction in the duration of stable operation. This indicated that the transition to an unstable regime was determined not by a single indicator, but by a system of interrelated variables.

Engineering verification of the identified patterns and applied interpretation of threshold states

An engineering review of the identified statistical and predictive relationships showed that they remain physically and operationally interpretable within the constraints typical of sand-prone wells. Scenario analysis in PIPESIM confirmed that combinations of characteristics previously associated with an increase in lost production and a transition to an unstable operational state correspond to an engineering-based deterioration in well operating conditions. This was most clearly evident when changes occurred in formation pressure, the condition of the filter zone, and the sand control configuration. Under such conditions, an increase in the pressure drop across the filter elements, an accumulation of downtime, a reduction in *SFR*, and an increase in the frequency of interventions indicated the system's transition to a regime of heightened hydrodynamic stress and an increasing likelihood of production losses. From an engineering perspective, the results showed that the unstable operating condition developed as a sequential change in operating mode. The increase in formation pressure drop at the initial stage was accompanied by an intensification of inflow; however, upon reaching the threshold range, it was combined with the mobilisation of mechanical impurities, an increase in local resistance in the near-wellbore zone, and an increase in the load on the filter elements. This, in turn, was accompanied by an increase in ΔP_f, a reduction in periods of stable operation without signs of sand production, and a transition to a regime in which operational interventions became recurrent. Under such conditions, a short-term improvement in productivity did not compensate for the accumulation of subsequent losses, as the system more frequently deviated from steady-state operation and required additional operations to restore flow or stabilise performance. Engineering verification confirmed that the previously identified statistical, regression and predictive relationships reflected the pattern of operational deterioration. Scenario analysis also made it possible to distinguish between a high-production regime and an unstable operational state, during which losses began to accumulate. With a moderate change in wellbore pressure and the maintenance of a controlled state of the filter zone, the system sustained a relatively stable level of production without a marked increase in downtime or the frequency of interventions. However, with a further intensification of the production regime and a simultaneous deterioration in sand control conditions, a change in the operational pattern was observed: an increase in short-term flow rate was followed by a rise in resistance, instability in inflow, and a subsequent decline in overall operational efficiency. Threshold conditions manifested in this zone, which were recorded in the statistical module through an increase in ΔP_f, DT_{6m}, a rise in the frequency of interventions, and a reduction in *SFR*. In engineering terms, this corresponded to a transition from an acceptable intensification regime to a regime in which continued operation without corrective measures was accompanied by higher losses than potential additional production. For the engineering interpretation of the identified threshold states and the assessment of technological response options, the results of the scenario modelling are presented in Figure 3.

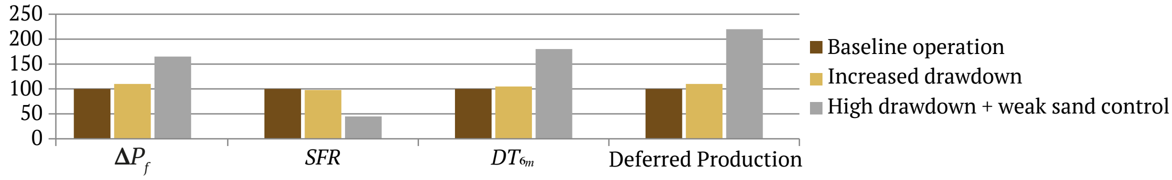

Figure 3. Engineering interpretation of scenarios for transition to an unstable regime under changing drawdown and sand control conditions

Note: values are normalised to the base scenario, set at 100, which allows for the comparison of relative changes in indicators across different units of measurement. The operational significance of a deviation from the 100 level depends on the nature of the indicator: for ΔPf, DT6m and Deferred Production, an increase relative to 100 indicates a deterioration in operating conditions, whereas for SFR, a decrease below 100 is unfavourable, as it reflects a reduction in the proportion of stable operation

Source: compiled by the author based on the results of simulation scenarios in Python/Jupyter and PIPESIM

As shown in Figure 3, the greatest deterioration in operating conditions was observed in scenarios combining increased reservoir depression with reduced sand control efficiency. Under these conditions, the ΔP_f index rose to 165, the DT_{6m} indicator to 180, and Deferred Production to 220 from a baseline of 100, whilst the *SFR*, conversely, fell to 45. This combination of changes indicated a concerted increase in hydrodynamic resistance, an accumulation of downtime and a rise in production losses, accompanied by a reduction in the proportion of stable operation. Under such conditions, the increase in pressure drop across the filter elements was accompanied by a reduction in stable operating intervals, an accumulation of downtime, and a shift in the operating regime towards a higher probability of lost production. Conversely, scenarios in which a change in production regime was combined with the maintenance or strengthening of sand control demonstrated a less pronounced change in regime: resistance increased more slowly, periods of stable operation remained longer, and the transition to an unstable operating state was shifted to a later stage. This indicated that the engineering interpretation of the identified thresholds was linked not only to the identification of a specific state but also to the distinction between regimes where intervention was already required and those where the possibility of adjustment still remained. The scenario analysis also confirmed the significance of temporal and operational indicators alongside hydrodynamic parameters. In previous stages of the analysis, *SFR*, DT_{6m} and the frequency of interventions had already demonstrated statistical and predictive significance. This was further confirmed in the engineering verification: a reduction in stable operation time and an accumulation of downtime reflected the moment when the system ceased to compensate for internal disturbances using its own margin of stability. Even with acceptable values for individual pressure or flow rate parameters, the well could already be entering a regime of deteriorating performance if the intervals of stable operation were shortening and the number of unscheduled interventions was increasing.

The engineering interpretation confirmed that monitoring only instantaneous operational indicators was insufficient; the approach to an unstable regime was more accurately identified through coordinated monitoring of the dynamics of operational stability. From a practical standpoint, this meant that threshold conditions were interpreted not as strictly isolated failure points, but as ranges of operational risk within which the system rapidly lost stability. The increase in ΔP_f, the decrease in *SFR*, the increase in DT_{6m} and the frequency of interventions collectively signalled that the current production regime was no longer economically or technologically viable. In the absence of corrective measures, this was accompanied not only by an increase in lost production, but also by an increased load on filtration systems, a higher probability of abrasive wear on equipment, and more frequent shutdowns. In this form, the results obtained could be interpreted taking into account the permissible operational limits and reliability requirements set out in API RP 14E (American Petroleum Institute, 1991) and ISO 17824:2009 (2009). To summarise the practical significance of the identified predictors and their link to potential operational measures, a practical interpretation is presented in Table 4.

Table 4. Practical interpretation of key predictors and recommended operational measures

Predictor	Operational significance	Associated risk	Recommended operational decision
Increase in ΔP_f	Increase in local resistance and deterioration of filtration conditions	Transition to an unstable inflow, accelerated accumulation of losses	Adjustment of the extraction regime, inspection of the filter zone, assessment of the need for cleaning or enhanced sand control
Reduction in *SFR*	Reduction in the proportion of stable operation without signs of sanding	Loss of operational stability, increased frequency of adverse incidents	Enhanced monitoring, early adjustment of operating parameters, reduction of drawdown at signs of accelerated degradation
Increase in DT_{6m}	Accumulation of downtime within a six-month window	Loss of operational continuity, increase in lost production	Revision of intervention tactics, transition from reactive to preventive maintenance
Increase in intervention frequency	Increase in operational instability and recurrence of faults	Increased costs, shorter intervals between overhauls	Optimisation of intervention strategy, investigation of causes of recurring faults, adjustment of operating regime
Deterioration in R_q and increase in ΔWC	Decrease in productivity and deterioration of inflow structure	Accelerated decline in production efficiency	Early assessment of production regime, comparison with the condition of the filtration zone and permissible operating conditions

Source: compiled by the author based on the results of a synthesis of computational, statistical and scenario-based results in Python/Jupyter and PIPESIM

As shown in Table 4, operational deterioration was associated with an increase in ΔP_f, a decrease in *SFR*, an increase in DT_{6m} and a rise in the frequency of interventions. The increase in ΔP_f reflected an increase in local resistance and a change in filtration conditions. The decrease in *SFR* indicated a reduction in the proportion of time spent in stable operation without signs of sanding. The increase in DT_{6m} indicated an accumulation of downtime within a six-month window, whilst the increase in the frequency of interventions indicated an increase in the number of instances of operational mode correction. The combined change in these indicators showed that the transition to an unstable operating state was accompanied by a simultaneous change in the hydrodynamic and operational characteristics of the system. Practical interpretation also showed that operational measures corresponded to the type of deviation identified. An increase in ΔP_f was associated with monitoring the condition of the filtration zone and sand control parameters. A decrease in *SFR* and an increase in DT_{6m} indicated a reduction in the duration of stable operating intervals and an accumulation of interruptions in production continuity. An increase in the frequency of interventions reflected a transition to a regime in which maintaining operational status required more frequent process adjustments. In this form, the identified predictors were used to identify conditions accompanied by a further increase in lost production.

Discussion

The results obtained showed that the shortfall in production from sand-prone wells was not caused by a single isolated anomaly, but rather by the combined effect of changes in several operational parameters. These included an increase in the pressure drop across the filter elements, a reduction in the proportion of stable operation, an accumulation of downtime, and an increase in the frequency of operational interventions. A similar approach is presented by A. Safaei *et al*. (2023), where chemical methods for controlling sand production were considered as one element of a sand control system, the effectiveness of which was determined by the properties of the formation, the conditions of application, and the well operating regime. This comparison showed that the transition to an unstable operating state was determined by the interaction of several factors and could not be reduced to a single indicator of deterioration in operating conditions. The most pronounced differences between stable and unstable intervals were associated with the rate of decline in flow rate, an increase in water cut, the accumulated duration of downtime, and a reduction in the proportion of time spent in stable operation without signs of sand production (Iskandarov *et al*., 2024; Kerimkhulle *et al*., 2025). These findings are consistent with the data of Z. Xu *et al*. (2024), where it was shown that the effectiveness of sand control was determined by a combination of material, technological and operational characteristics, rather than solely by the choice of a single reagent or treatment method. A comparison with the results obtained showed that the parameters reflecting the dynamics of the operating regime over time were of comparable significance to instantaneous hydrodynamic indicators, as they recorded the system's transition from an acceptable regime to the accumulation of production losses. The greatest contribution to the change in the volume of lost production was made by ΔP_f, *SFR*, DT_{6m} and the frequency of interventions, whilst R_q and ΔWC complemented this configuration as derivative indicators of mode deterioration. In the work by X. He *et al*. (2024), technologies for the prevention and control of sand ingress were also examined through a combination of rock failure causes, production mode and the limitations of the technical solutions employed. This comparison showed that the identified predictors formed an interconnected system of operational characteristics, through which operational deterioration was accompanied by an increase in the volume of lost production. Within this system, the increase in local resistance in the sand control zone occupied a distinct position.

The increase in pressure drop across the filter elements was associated with a rise in the volume of lost production and simultaneously reflected a change in filtration conditions within the sand control zone. A similar relationship was presented by C. Ma *et al*. (2023), where numerical modelling of a prepacked gravel screen demonstrated that sand retention and changes in hydrodynamic resistance should be considered jointly, as an increase in the resistance of the filtration system affected the operational condition of the well. In this context, ΔP_f was considered in statistical, regression and predictive analyses as an indicator linked to the engineering logic of the sand control system's operation. A similar result was presented by N.A. Ahad *et al*. (2020), where the selection of the filtration screen took into account the need for simultaneous assessment of retention capacity and hydraulic losses. A similar relationship was demonstrated by N.I. Ismail *et al*. (2021), where modelling of particle motion in the flow and their retention showed a link between changes in these conditions and the redistribution of resistance in the filtration screen zone. A comparison showed that ΔP_f could be regarded not only as a current hydrodynamic parameter, but also as an indication of a transition to a regime in which the deterioration of filtration conditions limited operational stability. In this regard, local resistance was considered not only as a diagnostic parameter, but also as a parameter related to the overall stability of well operation.

The reduction in the proportion of stable operation without signs of sand production and the accumulation of downtime were no less significant than instantaneous pressure and flow rate indicators (De Padova *et al*., 2018). These conclusions were consistent with the findings of H.B. Mahmud *et al*. (2020), where an intelligent sand control system was designed to enable the timely identification of risk and the selection of a response strategy before the situation escalated into more costly operational disruptions. A comparison with the results of the study showed that *SFR*, DT_{6m} and the frequency of interventions could be interpreted as indicators of changes in operational stability, rather than merely as secondary consequences of disruptions that had already occurred. From this perspective, minimising lost production was linked not to a single corrective action, but to the choice between a sand control strategy and a sand management strategy, depending on the combination of risks and operational constraints. These findings were consistent with the data presented by E. Araujo-Guerrero *et al*. (2021), where the choice between the two approaches was based on an assessment of the probability of sand production, production constraints and the operating conditions of a specific well. This comparison showed that the identified predictors were used not only to identify an already established deterioration in operating conditions, but also to justify the operational response. In this regard, the frequency of interventions and the accumulation of operational disruptions were interpreted as signs of a transition to a less stable operating regime.

The results of scenario-based and applied interpretation showed that an increase in the frequency of interventions and the accumulation of downtime accompanied the transition from an acceptable operating regime to a state in which losses began to rise faster than the potential additional production. These findings were consistent with the data presented by N. Kerya *et al*. (2022), where the strategy for managing sand production at an offshore field was viewed as a system for the early detection of signs of regime deterioration and timely intervention before the transition to more costly operational disruptions. In the context of the results obtained, the frequency of interventions was considered not only as an operational indicator but also as a sign of a change in the stability of the regime. This allowed the mechanisms of deterioration to be analysed not only through operational parameters but also through the dynamics of sand transport within the production system. In this context, changes in flow rate, an increase in local resistance and the subsequent deterioration of the operating regime were associated with more complex dynamics of sand transport than could be explained solely by the current state of the bottomhole zone. These findings were consistent with the data of Z. Wang *et al*. (2025), where the migration of sand particles in the wellbore system was analysed based on experiments and numerical modelling and linked to changes in their movement trajectories, accumulation conditions, and the formation of local flow disruption zones. A similar relationship was observed in the field study by Y. Xiao *et al*. (2024), where sand production in wells with sliding couplings without a sand control system was linked to a combination of the reservoir's geomechanical properties, well completion design and operating conditions. In this context, signs of sand production translated into practical production constraints, indicating that the deterioration in production regime arose not only as a local filtration problem but also as a consequence of the interaction between formation conditions, wellbore configuration and the nature of the production flow. A similar approach was presented by S.K. Subbiah *et al*. (2021), where the causes of sand production and methods for predicting it were examined through a combination of matrix failure, flow characteristics and operating conditions. This comparison showed that an increase in ΔP_f, a deterioration in R_q and an increase in the probability of lost production could reflect not only a general deterioration in operating conditions, but also a redistribution of sand transport processes within the production system. In this regard, the system of predictors was considered as an integrated operational configuration rather than as a set of isolated variables.

The engineering interpretation of the identified relationships was further correlated with scenario modelling in PIPESIM: a combination of increased formation pressure and deteriorating sand control conditions was accompanied by an increase in ΔP_f, a decrease in *SFR*, an increase in DT_{6m}, and a higher probability of production shortfall. These findings were consistent with the results of M. Adil Issa *et al*. (2022), where a reduction in the risk of sand production was linked to the consideration of geomechanical and operational constraints, including allowable depression and changes in formation stability as it is depleted. A similar relationship between sand retention conditions and the filtration system regime was observed by C. Ma *et al*. (2021), where the properties of pre-packed sand control screens were examined in terms of the ratio of sand retention to flow capacity. This comparison showed that the statistical and predictive relationships were confirmed by engineering data within scenarios reflecting the operational constraints of sand-prone wells. Comparison with the results of the study showed that a data-driven approach to minimising lost production gained practical significance whilst maintaining the engineering interpretability of the model's indicators. Unlike studies focused primarily on describing individual control methods or specific technical solutions, this analytical framework combined statistical comparison, regression analysis of factor contributions, predictive modelling and engineering verification within a unified analytical scheme. This made it possible to consider the identified system of predictors as a basis for the earlier detection of unstable operational states and for adjusting the production regime before the transition to a sustained accumulation of production losses.

Conclusions

The results of the study indicate that the lost production in sand-prone oil wells in the Caspian region, including those in Azerbaijan, was not caused by a single localised failure, but rather by a combination of interrelated operational changes affecting the production, hydrodynamic and operational characteristics of the well. A comparison of stable and unstable production intervals across a dataset of 48 wells and 1,728 monthly observations revealed that the transition to an unstable production state was accompanied by a decline in oil production, increased water cut, a rise in the pressure drop across the filter elements, an accumulation of downtime, and an increase in the frequency of operational interventions. Derivative indicators, including R_q, ΔWC, $\Delta P w_h$, DT_{6m} and *SFR*, confirmed that the deterioration in operating conditions was evident not only in the absolute values of the parameters but also in the directional dynamics of their change over time.

Regression analysis established that the greatest contribution to the change in the volume of lost yield was made by ΔP_f, *SFR*, DT_{6m} and the frequency of interventions. In the multiple linear regression model, the coefficients for these variables were 0.34, -0.32, 0.29 and 0.25 respectively, whilst the model's explanatory power reached $R^2 = 0.71$. In the peak regression, the same directions of influence and coefficients of similar magnitude were retained, confirming the stability of the identified relationships. It was thus established that an increase in local resistance, a reduction in the proportion of stable operation and an accumulation of downtime are directly linked to an increase in production losses and can be regarded as key predictors of operational deterioration. The machine learning module complemented the results of the statistical and regression analysis. In the task of classifying unstable operational states, the Gradient Boosting model demonstrated the best performance, with an Accuracy of 0.91, Recall of 0.89, Precision of 0.88, and an F1-score of 0.88. In the task of forecasting lost production, the XGBoost model provided the highest accuracy, with an MAE of 2.18 m^3/month, an RMSE of 3.04 m^3/month, and an R^2 of 0.79. Feature ranking showed that ΔP_f, *SFR*, DT_{6m}, intervention frequency and rate of decline in flow rate retained the greatest significance in the models. This confirmed that the unstable operational state was described by a system of interrelated parameters, rather than a single isolated indicator. Engineering verification in PIPESIM confirmed the physical interpretability of the identified patterns. Scenario analysis showed that a combination of increased formation pressure and deteriorating sand control conditions was accompanied by an increase in ΔP_f, a reduction in stable operating intervals, an accumulation of downtime, and a shift in the operating regime towards a higher probability of lost production. This allowed the threshold states to be interpreted not as isolated failure points, but as ranges of operational risk, upon reaching which continued operation without corrective measures was accompanied by increasing losses.

Thus, the reduction of production losses in sand-prone wells is linked to a shift from reactive responses to disruptions that have already occurred to analytically grounded management of the operating regime based on operational data, statistical models, machine learning algorithms and engineering verification of scenarios. Prospects for further research involve expanding the empirical database, verifying the robustness of the proposed approach under various sand-related conditions, and comparing its predictive results with other modern models for the analysis and predictive management of lost production.

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Підхід на основі аналізу даних для мінімізації перерв у видобутку на нафтових свердловинах, схильних до запіскування

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Анотація. Метою дослідження було розроблення аналітичного підходу до мінімізації втрат видобутку в нафтових свердловинах, схильних до запіскування, на основі експлуатаційних даних з Каспійського регіону, включаючи об'єкти в Азербайджані. Методологія дослідження базувалася на емпіричному аналізі щомісячних даних про видобуток із 48 діючих свердловин за період 2024-2025 рр. і включала порівняння стабільних та нестабільних інтервалів видобутку, кількісну оцінку впливу експлуатаційних факторів на втрати видобутку, прогнозне моделювання нестабільних станів та втрат видобутку, а також інженерну верифікацію виявлених закономірностей за реальних експлуатаційних обмежень. Було встановлено, що перехід до нестабільного експлуатаційного стану супроводжувався зниженням нафтовидобутку на 23,5 %, збільшенням водної фракції на 47,9 %, зростанням перепаду тиску на фільтрувальних елементах на 69,8 %, збільшенням тривалості простоїв у 3,8 рази та зростанням частоти експлуатаційних втручань на 154,5 %. Статистичне порівняння показало, що найвиразніші відмінності між стабільними та нестабільними інтервалами були пов'язані з темпами зниження дебіту, зростанням вмісту води, сумарною тривалістю простоїв протягом шестимісячного періоду та зменшенням частки стабільної видобутку без ознак виходу піску. Регресійний аналіз показав, що найбільший внесок у зміну втрат видобутку зробили перепад тиску на фільтруючих елементах, частка стабільної роботи, сумарний час простою та частота втручань, тоді як у блоці прогнозного моделювання найкращі результати продемонструвала модель XGBoost із середньою абсолютною похибкою 2,18 $м^3$ на місяць та коефіцієнтом детермінації 0,79. Практичне значення отриманих результатів полягає в можливості їх застосування в системах моніторингу видобутку та управління експлуатацією свердловин, схильних до пісковиділення, що дозволяє здійснювати раннє виявлення нестабільних умов, обґрунтовувати експлуатаційні втручання та коригувати інтенсивності видобутку з метою мінімізації втрат видобутку

Ключові слова: експлуатаційна нестабільність; опір фільтрації; сукупний час простою; частота експлуатаційних втручань; частка стабільної роботи; прогнозне моделювання; втрати видобутку