



Research article

Post-pressure monitoring and evaluation of horizontal wells using pressure-based analysis

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Abstract: Horizontal well post-pressure monitoring is important in testing wellbore integrity, reservoir response, and stability after interventions involving pressure. However, existing pressure-based evaluation methods lack systematic integration to capture transient behavior and translate pressure dynamics into actionable well condition assessments. The quantitative description of post-pressure behavior is aided by smoothed pressure trends, rolling variance, and derived stability indices, whereas the statistical approach to detect abnormal pressure deviations is based on the Z-score. This study optimized horizontal well monitoring, supporting sustainable energy by enhancing production efficiency and minimizing risks. A key finding of this study is the development of a clear rule-based decision framework that transforms pressure-derived metrics into operationally meaningful well condition states (*stable*, *warning*, and *risk*), shifting into a quantitative analysis and field-level decision-making. The proposed framework was confirmed with real post-pressure information from a horizontal oil well (Well No. 807). The proposed framework contributes to sustainable energy and environmental solutions by enabling reliable post-pressure well monitoring, improving operational efficiency, reducing intervention risks, and supporting optimized resource utilization in horizontal well systems. The results indicate a clear transition from initial transient pressure behavior to a stable equilibrium state, with approximately 65% in the *stable* category, 25% in the *warning* category, and 10% in the *risk* category. In addition, the role of visual imaging logging is considered at a conceptual level due to the absence of real imaging data, intended to support future interpretation of pressure anomalies.

Keywords: horizontal wells; post-pressure monitoring; pressure analysis; anomaly detection; stability index; rule-based classification

1. Introduction

Horizontal wells represent a significant advancement in modern oil and gas production, where more reservoirs are connected, and more hydrocarbons can be recovered. The operational efficiency is also higher than in traditional vertical wells [1]. Horizontal wells increase the exposure to heterogeneous reservoirs and allow more effective drainage of hydrocarbons by extending laterally within productive formations. Nevertheless, this long wellbore geometry also causes serious complexity in pressure behavior and flow dynamics as well as reservoir-wellbore interaction [2]. Multiphase flow along the horizontal section is often non-uniform, which creates pressure differences, local inflow differences, and temporary pressure changes, which are hard to interpret with traditional monitoring systems [3]. These difficulties are especially acute at the post-pressure stage, which follows pressure-modifying interventions (hydraulic fracturing, stimulation, pressure testing, or engineered drawdown). During this period, the well transitions from a disturbed state to equilibrium, and any small deviations in pressure can be an indication of a reservoir connectivity problem, flow limit, or wellbore early destruction. Failure to properly analyze post-pressure behavior may result in unidentified operational risks, an inefficient choice of production strategy, and the deterioration of well performance over a long period. Therefore, it follows that effective post-pressure surveillance should be used to assess well integrity, identify abnormal behaviors, and facilitate informed decision-making in horizontal wells. With reservoirs evolving to be more sophisticated and with the shift toward unusual and marginal fields, the necessity to find stable and data-driven post-pressure evaluation procedures has never been as urgent [4].

Conventional systems of horizontal well evaluation use pressure, production rates, and general interpretations of well tests to draw conclusions about the performance and operation conditions of the reservoir. Although downhole pressure measurements can offer crucial information on the energy and depletion trend of the reservoir, measurements of pressure alone do not always have the spatial resolution to detect localized wellbore characteristics such as fractures, debris, partial blockages, or unequal inflow along the horizontal section [5]. Further, using multiphase flow effects, operational disturbances, and transient behaviors often affect pressure signals, therefore causing ambiguity and occasional misinterpretations. Reliable post-pressure monitoring of horizontal wells supports sustainable energy production by improving operational efficiency, minimizing resource losses, and reducing environmental risks. In order to overcome these limitations, complex logging equipment, i.e., array production logging, acoustic reflection imaging, and permeability logging, has been developed to provide spatial and structural information of horizontal wells. Among these, visual and imaging-based logging methods can potentially allow an observation of the conditions in wellbores directly and correlate them with pressure behavior [1]. However, in practice, pressure data and imaging data are most commonly interpreted separately [6,7].

The recent development of data analytics and machine learning has introduced new approaches for enhancing horizontal well monitoring and anomaly detection. Pressure forecasting, flow regime identification, and early warning systems on abnormal well behavior have been conducted using data-driven techniques. Statistical and machine learning algorithms enable the identification of hidden patterns in vast amounts of well data, increasing the sensitivity to subtle deviations that might

otherwise remain unseen [8]. Nonetheless, a lot of current research is concerned with predictive accuracy instead of interpretability, which is based on the use of sophisticated models that act as black boxes and cannot be easily verified or applied in a real field setting. Moreover, much of the literature relies on simulated or idealized data, which cannot be extrapolated to real-world horizontal wells that are noisy, include missing data, and have operational variability [9]. Notably, as the methods of detecting anomalies become more widespread, little research turns the identified anomalies into operative categories of well conditions that may be directly utilized in operational decision-making. Inadequate post-pressure evaluation criteria and interpretable classification schemes are one of the research gaps [10]. These limitations highlight the need for an integrated and interpretable framework specifically designed for post-pressure monitoring and evaluation of horizontal wells.

In order to overcome these issues, the present research suggests a detailed post-pressure monitoring and evaluation framework of horizontal wells that incorporates quantitative pressure analysis, statistical anomalies detection, rule-based categorization, and a conceptual discussion of visual imaging logging for future integration. The proposed methodology starts by isolating the post-pressure stage from the data of continuous pressure wells, so that analysis is done on the most important period to analyze stability. Smoothing of the pressure trends, pressure derivative (dP/dt), and rolling variance-based stability indices are then calculated to describe global and local pressure behavior. To detect anomalies, the statistical Z-score method is followed to allow the efficient detection of abnormal deviations in pressure, not relying on a model that can be trained. These quantitative indicators are then grouped together using a rule-based classifier in order to provide labels of interpretable well condition, which include *stable*, *warning*, or *risk*, to help directly support operational planning and risk management. Ultrawide-angle visual imaging logging offers conceptual integration, which can be used to generate an extra layer of interpretative information, with identified pressure anomalies related to potential wellbore or reservoir features. The proposed framework closes the gap between advanced analytics and real field implementation, as it focuses on interpretability, reproducibility, and real-world applicability. This approach provides a systematic and decision-oriented solution to the post-pressure evaluation of horizontal wells' functioning under complex and uncertain conditions. This study proposes a unified and interpretable post-pressure evaluation framework for horizontal wells that integrates pressure trend analysis, stability assessment, anomaly detection, and rule-based classification into a single workflow. Unlike existing approaches that primarily focus on individual techniques, the proposed method emphasizes the post-pressure phase and translates analytical outputs into actionable operational decisions. Furthermore, the framework is validated using real field data and is designed to be computationally efficient and suitable for practical engineering applications.

1.1. Objectives of the study

The primary objective of this study is to develop a systematic and robust post-pressure monitoring and evaluation framework for horizontal wells' post-pressure monitoring and evaluation based on routinely acquired pressure and production data. The purpose of the study is to quantitatively describe the post-pressure well and reservoir response by comprehensively examining pressure trends, pressure derivative (dP/dt), and stability indices, allowing a better insight into flow dynamics and pressure recovery processes. Another goal is to determine the presence of abnormal pressure deviations during the post-pressure stage through an anomaly detection strategy that is statistically driven to facilitate

early detection. A comparative analysis of pre-pressure and post-pressure functioning is also used as an evaluation tool of the effectiveness of pressure stabilization. Furthermore, the study aims to categorize post-pressure well conditions into intuitive and understandable operations (stable, warning, and risk) using a transparent rule-based decision-making framework to facilitate its applicability in field decision-making. Lastly, the study discusses the potential integration of visual imaging logging as a future enhancement with pressure-based analysis to provide a better understanding of wellbore conditions and possible structural anomalies, allowing a more comprehensive understanding of the performance of horizontal wells.

1.2. Contributions

This study presents an interpretable and application-oriented framework for post-pressure evaluation of horizontal wells by integrating multiple statistical indicators into a unified system. The main contribution lies in transforming conventional analytical techniques into a practical decision-support tool through rule-based classification of well conditions (stable, warning, risk). The proposed approach ensures transparency, reproducibility, and direct applicability in real field environments using real well data.

The paper is organized as follows: Section 1 introduces the research background, motivation, objectives, and contributions. Section 2 reviews related work on pressure monitoring, logging technologies, anomaly detection, and integrated evaluation frameworks for horizontal wells. Section 3 presents the proposed methodology, including pressure trend and gradient analysis, stability evaluation, anomaly detection, rule-based well condition classification, and conceptual integration of ultrawide-angle visual imaging logging. Section 4 discusses the experimental results and their operational implications. Finally, Section 5 concludes the paper and outlines future research directions.

2. Literature review

The monitoring and evaluation of horizontal wells after pressure has been of growing interest because of the complexity of the flow behavior, the heterogeneity of the reservoirs, and issues with an accurate identification of operational abnormalities. Recent studies have underlined a combination of monitoring pressure, logging devices, machine learning, and multiparameter evaluation systems to enhance the efficiency of all wells. These are the four broad themes that can be identified in the literature:

2.1. Pressure monitoring and post-pressure analysis

Proper tracking of the reservoir pressure is needed to assess post-pressure well performance and identify abnormal conditions. Meng L, et al [11] created a real-time hydraulic fracturing pressure diagnostic model in highly deviated wells to identify the pressure deviation in real-time as well as the risks associated with the operation process. Liang J, et al [12] showed that a combination of well logging and mud logging, using machine learning, is better in predicting formation pressure to improve reservoir evaluation at post-pressure phases. Li L, et al [13] designed a theoretical framework on the concept of productivity analysis in offshore low-permeability horizontal wells, but also stated the significance of post-pressure evaluation in defining well performance and forecasts of production [8].

Luo R, et al [14] used array production logging to model the multiphase flow behavior in the horizontal wells and showed how persistent measurements of production parameters can be used to understand the post-pressure conditions of the wellbore [9].

2.2. Logging technologies and imaging integration

Sophisticated logging equipment has significantly enhanced the characterization of wellbore and reservoir conditions. Kang Z, et al [15] developed an innovative azimuthal laterolog resistivity tool that could be used in an oil-based mud environment to provide better subsurface resistivity estimates to deviated and horizontal wells. In the study by Li N, et al, [16] a prototype of downhole testing of permeability logging was successfully performed, which allows the real-time assessment of formation properties. Moreover, Li N, et al [17] emphasized the capabilities of acoustic reflection imaging logging to identify fractures, heterogeneities, and other structural objects, providing a background to visual data and pressure measurement integration. In horizontal wells, Song H, et al. [18] used machine learning on several array production logging data, which enhanced the interpretation of flow inputs of various well sections.

2.3. Anomaly detection and machine learning approaches

Detection of anomalies in horizontal wells is essential to ensure that operational problems, reservoir heterogeneity, and flow aberrations are detected early enough. Researchers have found that one-class classifiers can be more effective than other multivariate time series anomaly detection methods due to the efficacy of a non-ML statistical framework in abnormal well behavior detection [19]. He Y, et al [20] demonstrated that machine learning methods are able to soundly anticipate reservoir rock characteristics like porosity using well logging information; such information can assist in identifying unforeseen changes in production. Al-alimi A, et al [21] proposed a framework of real-time monitoring of smart wells on a surface level, in which there are no large numbers of downhole sensors, and the system relies on predictive models to identify abnormalities in pressure and flow parameters.

2.4. Integrated evaluation frameworks for horizontal wells

More recent tendencies have focused on the integration of various sources of information so as to offer a holistic assessment of the performance of horizontal wells. Liang J, et al [12] have shown that by combining well logging and mud logging with machine learning, one can develop a more stable structure of formation pressure prediction, which enables the assessment of several parameters simultaneously. Luo R, et al [14] also emphasized the benefits of array production logging in the measurement of multiphase flow, which offers information that can be combined with pressure and imaging to achieve better interpretation. Song H, et al [18] also indicated that using machine learning on array production logging enhances the segmentation and classification of flow zones and allows the combination of decisions on well management. Taken together, these authors showed that an integration of pressure monitoring, logging technologies, and machine learning could allow a better understanding of horizontal well behavior, as it is applied to the development of post-pressure evaluation frameworks such as the one presented in the current study. Despite these advancements,

most existing studies focus on individual analytical techniques and lack an integrated framework for post-pressure evaluation. Additionally, limited attention has been given to transforming analytical results into interpretable well condition classifications for operational decision-making. This highlights the need for a unified and application-oriented approach.

2.5. Comparative analysis of existing monitoring frameworks

Horizontal well monitoring approaches, in practice, can be grouped more or less into statistical monitoring methods, machine learning–assisted analysis, and integrated evaluation frameworks. Statistical methods are clear and computationally light and can flag pressure variations and anomalies [19], but sometimes can only track one indicator at a time, without turning the outcome into an operational well-condition judgment [20]. Machine-learning analysis usually obtains better prediction and anomaly detection but tends to lean on big training data collections, and, for field engineers, the explanations can feel a bit opaque [14]. Integrated monitoring frameworks try to weave multiple data sources with several analytical tools, so that the well performance picture is wider; however, many publications end up concentrating on prediction, reservoir characterization, or production optimization, rather than doing systematic post-pressure evaluation [12]. In contrast, the proposed framework is laid out specifically for post-pressure monitoring and assessment of horizontal wells. It brings together pressure trend analysis, pressure derivative analysis, stability assessment, statistical anomaly detection based on the Z-score method, and a rule-based well-condition classification, all within one unified workflow.

2.6. Research gap

In spite of the massive progress in pressure monitoring, logging technologies, and machine learning–based anomaly inspection, there are still some limitations to these studies. Although acoustic reflection and array production logging can give useful information on wellbore conditions, not many studies present full data on ultrawide-angle visual imaging with pressure trends to confirm anomalies. The majority of methods are aimed at one variable, i.e., pressure tendencies, production logging, or the properties of the formation, instead of offering a multiparameter system of complete post-pressure evaluation. Also, most publications are based on simulations or idealized data, which restricts their use to actual horizontal wells in complex field conditions. Current approaches also do not provide powerful approaches to isolating the post-pressure process and establishing transient behaviors, which are essential in operational decision-making. Lastly, whilst machine learning is being applied more and more to detect anomalies, not many methods turn these findings into practical well condition categorizations (e.g., stable, warning, risk).

In order to fill these gaps, the proposed post-pressure monitoring and evaluation system incorporates multiparameter pressure analysis, stability assessment, anomaly detection, and conceptual ultrawide-angle visual imaging logging into one system. The model was able to measure the transient behavior and abnormal zone through the segmentation of the post-pressure stage and an examination of smoothed trends in pressure and pressure derivative (dP/dt) and stability indices. These analyses are translated into operational conditions through statistical anomaly detection using the Z-score method alongside rule-based classification in order to produce actionable well conditions. This holistic model

uses real well data and multi-source data to provide an effective, reproducible, practical framework to determine the performance of horizontal wells. An overview of recent research on horizontal well pressure monitoring and logging is presented in Table 1.

Table 1. Summary of recent studies on horizontal well pressure monitoring and logging.

S. No	Author and year	Study focus/technology	Method/approach	Key findings/contribution
1	Song et al. (2025) [18]	Multiple array production logging	Machine learning-based interpretation	Improved flow zone identification and segment-specific production analysis in horizontal wells
2	Kang et al. (2025) [15]	Logging while drilling	Azimuthal laterolog resistivity tool for oil-based mud	Enhanced resistivity measurements for deviated and horizontal wells
3	Ning Li et al. (2024) [16]	Permeability logging	Downhole prototype testing	Successful real-time permeability evaluation for improved reservoir characterization
4	Li et al. (2024) [17]	Acoustic reflection imaging logging	Processing and interpretation methods	Detects fractures, heterogeneity, and structural anomalies in wellbores
5	Meng et al. (2025) [11]	Hydraulic fracturing pressure prediction	Real-time diagnostic modeling	Enables timely detection of pressure deviations and operational risks in highly deviated wells
6	Liang et al. (2025) [12]	Formation pressure prediction	Machine learning with integrated well and mud logging	Accurate pressure prediction, enhancing reservoir evaluation during post-pressure phases
7	Li et al. (2024) [13]	Productivity evaluation in horizontal wells	Modified theoretical model	Evaluates well productivity in low-permeability reservoirs and supports operational planning
8	Luo et al. (2023) [14]	Array production logging	Multiphase flow analysis in horizontal wells	Provides continuous monitoring of post-pressure flow behavior and wellbore performance
9	Al-Alimi et al. (2025) [21]	Surface-based monitoring	Smart wells without downhole sensors	Real-time anomaly detection and well performance assessment
10	Fernandes et al. (2024) [19]	Anomaly detection	One-class classifiers in multivariate time series	Identifies abnormal operational behavior in oil-producing wells
11	He et al. (2025) [20]	Reservoir rock porosity prediction	Well logging and machine learning	Accurate porosity prediction aiding anomaly detection and reservoir characterization

3. Methodology

The purpose of this research is to establish a robust post-pressure monitoring and evaluation system for horizontal wells to support a quantitative evaluation of well performance, early anomaly, and actionable classification of well conditions. The experiment uses operational data of Well No. 807, a horizontal well in a mature oil field in the north of Russia. The dataset corresponding to Well No. 807 does not include detailed operational records specifying the exact type of pressure-related

intervention or the precise completion time of the operation. However, the pressure-time profile exhibits a clear transition from a highly fluctuating regime to a progressively stabilized trend. This transition behavior is consistent with the expected response following the completion of a pressure-related operation and is used as a reference for stage identification. The post-pressure stage is defined based on the observed pressure-time characteristics of the well. The starting point is identified as the time at which high-frequency fluctuations associated with operational disturbances diminish, and a gradual stabilization pattern begins. This point represents the transition from transient, operation-influenced behavior to reservoir-dominated pressure response. The data includes the daily record of the production rate of oil, gas, and water, the overall rate of liquid production, the rate of water cut, the dynamic fluid level, working hours, and the downhole reservoir pressure. Raw data are extensively preprocessed to address missing values, noise, and inconsistencies. Linear interpolation and statistical filtering are applied to generate a continuous and reliable time series to be further analyzed. Thresholds and slices of time separate the post-pressure stage to isolate the periods of interest in the operation to be analyzed. Smoothing pressure trends and gradients are computed to describe the wellbore and reservoir behavior, and rolling variance and stability indices offer quantitative data on the pressure equilibrium and system stability. The Z-score method is used to identify abnormal pressure events and transient behaviors, which allow identifying the existence of operational deviations and anomalies in the reservoirs. The pressure trends, gradients, and anomalies detected can be interpreted to determine the flow regimes as stabilized, transitional, and abnormal. Lastly, the framework conceptually combines the ultrawide-angle visual imaging logging with quantitative pressure analysis. The proposed method integrates pressure trend analysis, pressure derivative evaluation, anomaly detection, stability assessment, and rule-based classification to support sustainable energy production and efficient resource management in horizontal wells. The multiparameter methodology assists in categorizing the overall well condition into actionable groups like *stable*, *warning*, or *risk*, which could give a reproducible, programmatically implementable decision support system on how operational planning and risk reduction can be achieved, besides a better understanding of horizontal well performance. Figure 1 shows the general flow of the methodology.

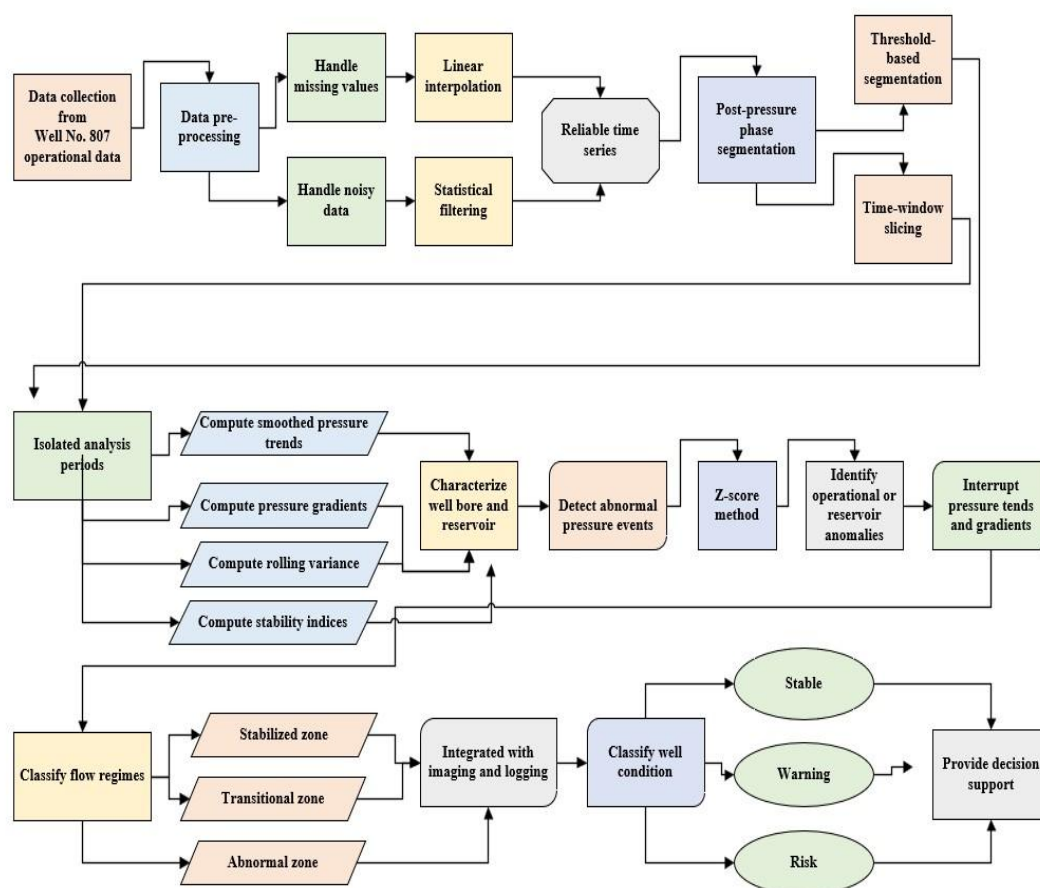


Figure 1. Workflow diagram of the proposed robust post-pressure monitoring and evaluation framework for horizontal wells.

3.1. Dataset collection

The dataset used in this study contains real operational data collected in an oil well (Well No. 807) in a mature oil field in north-western Russia. It was drilled in 2013, with a well depth of approximately 2400 M, having been under continuous monitoring in production. The dataset includes time series measurements on a daily basis, which defines the nature of operations, production, and the reservoir of the well. Recorded parameters are the oil production rate, total liquid production rate, gas production rate, water production rate, water cut, dynamic fluid level, and reservoir pressure monitored by means of a downhole sensor installed in the pumping system. All these parameters are used to describe the behavior of the multiphase flow in the wellbore and the depletion behavior of the reservoir when it is operated over a long period of time. Physically, the production of oil wells is governed by the principles of mass conservation, and the overall fluid that is produced is made up of oil, water, and gas. This connection can be stated as in Eqs (1) and (2):

$$Q_l(t) = Q_o(t) + Q_w(t) \quad (1)$$

$$WC(t) = Q_w(t) \times 100 \quad (2)$$

where $Q_l(t)$ is the total rate of production of liquid, $Q_o(t)$ is the rate of production of oil, $Q_w(t)$ is the rate of production of water, and $WC(t)$ is the percentage of water cut at a given time.

The pressure of the reservoir $P(t)$, expressed in atmospheres, is the key measure of the reservoir energy and has a direct impact on production performance. As production is ongoing, the depletion of pressure causes decreased oil production and high water production, which is a characteristic of the maturity of the reservoirs and the condition of the well. The data gathered is structured in the form of a chronological time series, forming the input of the proposed analytical framework. Before post-pressure monitoring and evaluation, the raw data is first processed by data preprocessing to overcome missing data, noise, and temporal inconsistency. This guarantees continuity of the pressure signal and the stability of later processing of pressure trends, stability, and anomalies.

Table 2. Dataset characteristics and missing data statistics.

Variable	Unit	Samples	Missing values	Missing ratio (%)
Reservoir pressure	atm	100	3	3
Oil production rate	m ³ /day	100	2	2
Water production rate	m ³ /day	100	2	2
Gas production rate	m ³ /day	100	1	1
Total liquid rate	m ³ /day	100	2	2
Water cut	%	100	1	1
Dynamic fluid level	m	100	4	4
Operating hours	h/day	100	1	1

Table 2 summarizes the characteristics of the dataset used in this study and provides a detailed assessment of data completeness for each monitored variable. The results indicate that the dataset contains a relatively low proportion of missing observations, with missing data ratios ranging from 1% to 4%. The dynamic fluid level exhibited the highest missing data ratio (4%), whereas gas production rate, water cut, and operating hours showed only 1% missing observations. Overall, the dataset demonstrates high completeness and reliability for post-pressure monitoring analysis. The identified missing values were subsequently reconstructed using linear interpolation to ensure continuity of the time series data before pressure trend analysis, stability evaluation, and anomaly detection.

3.2. Data preprocessing

Raw oil well operational data usually presents some missing operational entries and measurement noise because of sensor limitations, transmission errors, and operational disturbances. Because proper pressure trend and stability evaluation require continuous and consistent time series, data preprocessing is carried out before post-pressure monitoring evaluation.

Table 3. Quantitative impact of interpolation and statistical filtering on dataset quality.

Metric	Raw data	After processing	Improvement
Dataset completeness (%)	98	100	2.00%
Pressure noise Std. Dev. (atm)	3.1	2.5	19.4% reduction
Pressure trend correlation	-	0.996	Preserved
Detected outliers	14	5	64.3% reduction
Missing records	16	0	100% recovery

Table 3 presents the quantitative improvements achieved through the preprocessing stage, including linear interpolation and statistical filtering. The results show that dataset completeness increased from 98% to 100% through the recovery of all missing records. Statistical filtering reduced the pressure-noise standard deviation from 3.1 to 2.5 atm, corresponding to a 19.4% reduction in measurement noise. Additionally, the number of detected outliers decreased from 14 to 5 observations, representing a 64.3% reduction while preserving the overall pressure-depletion trend, as indicated by the high pressure-trend correlation coefficient of 0.996 between the raw and processed datasets. These findings confirm that the preprocessing procedures significantly improved data quality without altering the underlying physical behavior of the reservoir pressure signal.

3.2.1. Handling missing values using linear interpolation

The time series produces missing pressure and production values that are estimated by linear interpolation to retain time continuity but not distort false trends. In case of a missing value at time t_k , bounded between known values at time t_{k-1} and t_{k+1} , the linear interpolation can be written as Eq. (3):

$$X(t_k) = X(t_{k-1}) + \frac{X(t_{k+1}) - X(t_{k-1})}{t_{k+1} - t_{k-1}} (t_k - t_{k-1}) \quad (3)$$

where $X(t)$ represents the measured parameter (e.g, pressure, production rate, or fluid level) at time t , and t_k denotes the time point with a missing value. This interpolation method preserves continuity in the time series while minimizing distortion of the original trend.

3.2.2. Statistical filtering for noise reduction

In order to minimize the role of random noise measurements and large fluctuations, some simple statistical filtering is done on the interpolated data. Statistical dispersion measurements based on the time series are used in determining the filtering process.

For each parameter $X(t)$, the mean μ and standard deviation σ are computed as in Eqs. (4) and (5):

$$\mu = \frac{1}{N} \sum_{i=1}^N X_i \quad (4)$$

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (X_i - \mu)^2} \quad (5)$$

where σ is the standard deviation, μ is the mean value of the dataset, and X_i represents the measured parameter at the i^{th} observation. The data points of abnormal deviations that exceed the acceptable levels in statistics are smoothed or not considered in further analysis. The effect of sensor spikes is reduced, and physically relevant pressure changes are retained by this process. Following linear interpolation and statistical filtering, the data is converted to a clean, noise-reduced, and continuous time series. The input is the preprocessed pressure and production data used in the post-pressure phase segmentation and further pressure trend, gradient, stability, and anomaly analysis.

3.3. Post-pressure phase segmentation

Post-pressure monitoring concerns the analysis of pressure behavior following pressure-related activities like well stimulation, pressure testing, or pumping modifications. The post-pressure phase has to be correctly identified in order to analyze wellbore stabilization, pressure tendencies, and anomalies. This stage takes the preprocessed pressure time series as the input.

3.3.1. Threshold-based segmentation

Active pressure operations are detected by keeping a threshold of phases that isolate the post-pressure phase used in segmentation. The transition point t_s is determined when the measured reservoir pressure $P(t)$ falls below a defined threshold relative to the initial pressure P_0 or exceeds a predefined operational limit, as shown in Eq. (6).

$$t_s = \min\{t \mid P(t) \leq P_{th}\} \quad (6)$$

where P_{th} represents the threshold pressure indicating the start of the post-pressure monitoring phase. All subsequent time series data points $P(t)$, $t \geq t_s$ are considered part of the post-pressure dataset. This ensures that the relevant data reflecting wellbore response after operations are analyzed.

3.3.2. Time-window slicing

To capture temporal variations within the post-pressure phase, the time series is further divided into uniform windows of length Δt . Each window W_j is defined as shown in Eq. (7):

$$W_j = \{P(t) \mid t_s + (j-1)\Delta t \leq t < t_s + j\Delta t\}, j = 1, 2, \dots, n \quad (7)$$

where n is the total number of windows in the post-pressure period. The local analysis of pressure trends, gradient, and stability is feasible with time-window slicing, and transient behaviors could be detected, which might not be observable in the entire dataset. The post-pressure phase decomposition creates a subset of the already processed pressure data, which is divided into time windows in turn to be analyzed in more detail. The two outputs are post-pressure time series $P(t)$, $t \geq t_s$ and windowed

data slices $W_1, W_2, \dots, W_n$ for local trend and anomaly evaluation. This split data is then used in the analysis of pressure trend and gradient, stability, and anomaly analysis.

3.4. Pressure trend and gradient analysis

The behavior of horizontal wells after pressure is analyzed by examining the temporal development of the reservoir pressure. Trends in pressure indicate how the reservoirs react with changes in pressure, the redistribution of the flow along the borehole, and the success of the post-pressure operations. The input of this step is the segmented and preprocessed dataset.

3.4.1. Pressure trend

The trend analysis begins with visualizing the pressure time series $P(t)$ to discover the overall trends, such as stabilization, gradual decrease, or sudden shift. High-frequency noise on the raw or fragmented time series may be removed with a moving average filter, as in Eq. (8):

$$\tilde{P}(t_i) = \frac{1}{2k+1} \sum_{j=i-k}^{i+k} P(t_j) \quad (8)$$

where $\tilde{P}(t_i)$ is the smoothed pressure at time t_i , and $2k + 1$ defines the window length for smoothing. This filtering preserves the overall trend while mitigating minor measurement fluctuations.

3.4.2. Pressure derivative (dP/dt) computation

To identify rapid changes in pressure, the temporal gradient dP/dt is computed. The discrete pressure derivative (dP/dt) is estimated using numerical differentiation, shown in Eqs. (9) and (10).

$$\left. \frac{dP}{dt} \right|_{t_i} \approx \frac{P(t_{i+1}) - P(t_i)}{t_{i+1} - t_i} \quad (9)$$

or, for improved accuracy with central differences:

$$\left. \frac{dP}{dt} \right|_{t_i} \approx \frac{P(t_{i+1}) - P(t_{i-1}))}{t_{i+1} - t_{i-1}} \quad (10)$$

where $P(t_i)$ represents the pressure at time t_i . Sudden deviations in the gradient indicate potential anomalies, rapid pressure drops, or wellbore disturbances.

3.4.3. Smoothed gradient analysis

A smoothed gradient brings persisting trends to the fore and makes it possible to detect significant changes in pressure without being influenced by temporary spikes in measurements, as shown in Eq. (11):

$$\frac{d\tilde{P}}{dt}(t_i) = \frac{1}{2k+1} \sum_{j=i-k}^{i+k} \frac{dP}{dt}(t_j) \quad (11)$$

This smoothed gradient highlights persistent trends and allows the detection of significant pressure transitions without being affected by transient measurement spikes. The output of this stage includes smoothed post-pressure trend $\tilde{P}(t)$, smoothed pressure derivative $(dP/dt) \tilde{dP/dt}(t)$, and identified areas of rapid pressure change to be analyzed further in stability evaluation and anomaly detection. Through the integration of smoothed pressure trend data with gradient data, the methodology can be used to characterize both global and local reservoir response and wellbore behavior in the post-pressure period.

3.5. Pressure stability evaluation

Analysis of pressure stability measures the level of equilibrium during post-pressure of a horizontal well. A stable pressure shows that the wellbore and reservoir have already achieved a near-steady condition following operations; an unstable pressure may result in further redistribution of fluids or possible anomalies. The input to stability analysis is the post-pressure time series, $P^*(t)$, serving as the input for stability evaluation.

3.5.1. Rolling variance calculation

To capture local pressure variability over time, a rolling variance is computed using a moving window of length w . The rolling variance $\sigma_r^2(t_i)$ at time t_i is expressed as shown in Eqs. (12) and (13):

$$\sigma_r^2(t_i) = \frac{1}{w} \sum_{j=i-w+1}^i [\tilde{P}(t_j) - \mu_r(t_i)]^2 \quad (12)$$

where $\mu_r(t_i)$ is the rolling mean within the same window:

$$\mu_r(t_i) = \frac{1}{w} \sum_{j=i-w+1}^i \tilde{P}(t_j) \quad (13)$$

This method quantifies short-term fluctuations in pressure and highlights periods of instability that may be masked in the overall trend.

3.5.2. Stability Index

A dimensionless Stability Index (SI) can be defined to standardize the rolling variance for comparison across wells or operational periods, as shown in Eq. (14):

$$SI(t_i) = \frac{\sigma_r(t_i)}{\tilde{P}_{\max} - \tilde{P}_{\min}} \quad (14)$$

where $\tilde{P}_{\max}$ and $\tilde{P}_{\min}$ are the maximum and minimum smoothed pressures in the post-pressure phase. Higher values of $SI(t_i)$ indicate greater variability and lower stability, while smaller values represent stabilized pressure conditions.

The output of this stage includes the rolling variance $\sigma_r^2(t)$ and rolling standard deviation $\sigma_r(t)$, which quantify short-term pressure fluctuations over the post-pressure monitoring period. In addition, a Stability Index $SI(t)$ is derived to provide a normalized and quantitative measure of pressure equilibrium within the reservoir-wellbore system. Depending on the time-varying pattern of these indicators, the post-pressure period is divided into stable, transitional, and unstable processes, which makes it possible to assess the performance of the well locally. Together, the results allow forming a strong analytical basis for further anomaly detection and make it possible to physically and interpretively assess wellbore behavior in post-pressure conditions. The key parameters used in the proposed framework are selected based on the characteristics of the pressure dataset to balance noise reduction and sensitivity to transient variations. The rolling variance window length is set to 10 data points, with a recommended range of 5–20, while the time-window segmentation length is chosen as 50 samples, with a typical range of 30–100 depending on data resolution. The stability threshold is defined as 0.02 based on normalized pressure variance, where values in the range of 0.01–0.05 effectively distinguish stable and unstable conditions. These parameter settings ensure consistent and reliable identification of pressure behavior across different operational scenarios.

3.6. Anomaly detection using Z-score

The process of detecting anomalies is essential to post-pressure monitoring because it defines abnormal pressure behavior, which can be the manifestation of wellbore problems, reservoir heterogeneity, fluid entry challenges, or disturbances in the operation. Earlier identification of these anomalies assists in preventing wellbore damage, optimizing the production process, and making decisions that guide the operations. The inputs of this analysis are the rolling smoothed pressure series and the stability index from Section 4.5 to detect anomalies. The Z-score method normalizes each pressure value against a mean and standard deviation of the post-pressure dataset to identify extreme deviations. For each pressure measurement $P(t_i)$, the Z-score $Z(t_i)$ is calculated as in Eq. (15).

$$Z(t_i) = \frac{P(t_i) - \mu_P}{\sigma_P} \quad (15)$$

where μ_P and σ_P are the mean and standard deviation of the post-pressure pressure series, respectively. Pressure points with absolute Z-scores exceeding a predefined threshold Z_{th} are classified as anomalies, as shown in Eq. (16).

$$\text{Anomaly}(t_i) = \begin{cases} 1, & |Z(t_i)| > Z_{th} \\ 0, & |Z(t_i)| \leq Z_{th} \end{cases} \quad (16)$$

A commonly used threshold in engineering applications is $Z_{th} = 3$, corresponding to ± 3 standard deviations, which captures rare extreme events while ignoring normal operational fluctuations. For example, if the post-pressure mean and standard deviation are $\mu_P = 120$ atm and $\sigma_P = 5$ atm, a pressure reading of $P(t_i) = 138$ atm would yield $Z(t_i) = 3.6$, exceeding the threshold and thus being classified as an anomaly.

The Z-score technique is most applicable in horizontal well monitoring because it is easy to interpret and understand; also, it is physically relevant, with large deviations usually meaning real events in the wellbore, such as fractures or inflow changes. In contrast to machine learning-based approaches, it does not need any training data or intricate parameter optimization and can be used with small and large datasets. It also provides a transparent and reproducible framework, which can be easily validated and incorporated in operational decision-making. The deliverables of this phase consist of a time series of Z-scores, binary anomaly indicators of each data point, and identification of abnormal pressure regions, which are later applied in the interpretation of the behavior of horizontal wells. This methodology allows a physically interpretable and programmable way of identifying abnormal pressure behavior in horizontal wells. The Z-score threshold is set to 3 in accordance with the standard $\pm 3\sigma$ criterion used in statistical analysis for identifying significant deviations from the mean. This selection enables effective discrimination between normal pressure variations and abnormal behavior within the post-pressure dataset. Lower threshold values increase the number of detected deviations by capturing smaller fluctuations, whereas higher threshold values restrict detection to only extreme variations. The selected threshold ensures stable and consistent identification of pressure anomalies under varying operational conditions.

3.7. Horizontal well behavior interpretation

To simplify the analysis of the behavior of horizontal wells, especially in the post-pressure phase, a number of simplifying assumptions are made to define an analysis that is practical and physically significant. The equations assume that the fluid flow in the horizontal well is mainly associated with the wellbore axis (x-direction), with fluid characteristics including density (ρ) and viscosity (μ) remaining constant throughout the post-pressure monitoring period. The wellbore cross-sectional area (A) is assumed to be a uniform cross-section, but in areas where fracture, blockage, or other structural anomalies occur, the actual effective cross-sectional area is different. Also, the effects of gravity are considered to be insignificant relative to those of pressure-induced flow in the horizontal section. Such assumptions give a point of reference between trends, gradients, and anomalies of pressure and the underlying behavior of flow so that the performance of wellbores and the response of a reservoir can be interpreted reliably.

In the case of flow of an incompressible fluid in the horizontal well, the flow itself can be characterized with the help of a single-dimensional mass conservation (continuity), as shown in Eq. (17).

$$\frac{\partial(\rho Av)}{\partial x} + \frac{\partial(\rho A)}{\partial t} = 0 \quad (17)$$

where ρ is the fluid density, A is the wellbore cross-sectional area, v is the flow velocity, x is the horizontal wellbore position, and t is time.

This equation indicates that changes in mass flow along the wellbore $[\partial(\rho Av)/\partial x]$ are balanced by temporal variations in fluid content $[\partial(\rho A)/\partial t]$, reflecting a pressure-driven redistribution of fluids along the wellbore.

The observation of the pressure trends, gradients, and stability indices, along with the identified anomalies, can be used to identify the different regimes of flow within the horizontal well. Areas with low rolling variance and few variations in pressure derivative (dP/dt) are said to be in the stabilized zones, meaning that the flow is quasi-steady and the pressure distribution line is quite homogeneous along the wellbore. Transitional zones are areas of moderate gradient variations and sporadic anomalies and indicate temporary redistribution of the flow or small heterogeneity within the reservoir. Conversely, areas with high-gradient variability and regular deviations are defined as abnormal and, in most cases, they are associated with fractures, variable inflow, or blockages, which lead to localized alterations in the effective flow area (AAA). This categorization has a strict way of identifying observed pressure behavior as being associated with the physical and operational conditions of the well.

Darcy's law for horizontal flow relates the volumetric flow rate to the spatial pressure gradient along the wellbore, as shown in Eq. (18).

$$q = -\frac{kA}{\mu} \frac{dP}{dx} \quad (18)$$

where q is the volumetric flow rate, k is the reservoir permeability, μ is the fluid viscosity, and dP/dx represents the pressure gradient with respect to the distance along the wellbore. Unlike dP/dt , which describes temporal pressure variations used in the monitoring analysis, dP/dx characterizes the spatial pressure distribution governing fluid flow in the reservoir. The fluid flow rate is directly governed by the pressure derivative (dP/dt) within the reservoir. Variations in pressure over time therefore reflect changes in flow behavior and subsurface conditions. In this study, pressure-based indicators such as stability index and rolling variance are interpreted as quantitative measures of flow stability. Higher fluctuations in pressure correspond to deviations from steady-state flow, indicating potential instability or disturbances in the reservoir system. Thus, the proposed diagnostic indicators are physically consistent with the underlying pressure–flow relationship.

The outputs of the horizontal well behavior interpretation include the categorization of post-pressure regions into stable, transitional, and abnormal wellbore zones. Moreover, the localized irregularity and patterns of wellbore performance can be identified by the use of spatial and time mapping of detected anomalies. Correlations between deviations in pressure, flow rates, and characteristics of wellbores are also drawn and serve to provide information on how a reservoir would behave and its efficiency. This step is a key background to a further incorporation with visual imaging logging and well condition classification, thus allowing an all-encompassing, physically intelligible, and programmably executable assessment of horizontal well performance.

3.8. Visual imaging logging integration

Although visual imaging logging is not used in this study, it can assist in taking direct measurements of wellbore conditions to augment pressure-based measurements. Even though the available data does not contain real imaging data, observed pressure effects can, in theory, be mapped

to wellbore features, including fractures, debris, or fluid entry points, in order to better interpret the well behavior. This correlation could be stated in a theoretical context as in Eq. (19).

$$F_i = f(P(t_i), I(t_i)) \quad (19)$$

where F_i represents the integrated feature at time t_i , $P(t_i)$ is the measured pressure, and $I(t_i)$ represents the imaging observation, if available. This conceptualization offers a platform for connecting pressure deviations with potential physical characteristics in the wellbore, which aids in the validation of future operating choices.

3.9. Well condition classification using a rule-based classifier

The last step is to convert the quantitative analyses into actionable well condition labels, which might serve as a guide to operating plans and risk management. This classification is based on three major indicators: stability of the pressure, frequency of the anomalies, and interpretation of the flow behavior. The stability of the pressure is determined by the rolling variance and the stability index, calculated based on the reservoir pressure; it gives an evaluation of the degree of consistency of the pressure. The frequency of anomaly is calculated by tallying and assessing the severity of the anomalies in Z-scores during the post-pressure stage, pointing to the existence of an outlier that can be due to operational or reservoir problems. Lastly, flow behavior based on the interpretation of pressure trends and analysis of gradient helps one understand the dynamic response of the horizontal well to gain a comprehensive understanding of its performance in order to make proper operational decisions. The following are the rules of classification, shown in Eq. (20).

$$\text{Well Condition} = \begin{cases} \text{Stable,} & SI(t) \leq SI_{th} \text{ and low anomaly frequency} \\ \text{Warning,} & SI_{th} < SI(t) \leq 2SI_{th} \text{ or moderate anomalies} \\ \text{Risk,} & SI(t) > 2SI_{th} \text{ or frequent/severe anomalies} \end{cases} \quad (20)$$

where SI_{th} is the predefined stability threshold used to distinguish stable, warning, and risk operating conditions. This classification process results in straightforward well condition labels, namely *stable*, *warning*, or *risk*, giving a direct evaluation of the performance of the well. A detailed account of pressure behavior and anomalies is also provided, from which a detailed overview of the well performance is obtained. This data is used as decision-support information, which allows for effective planning and risk reduction strategies. All in all, this methodology is such that well evaluation is quantitative, reproducible, and can be done programmatically based on the current dataset available; that is why this is a practical tool in operational management. Figure 2 below illustrates the architecture diagram of the rule-based classifier.

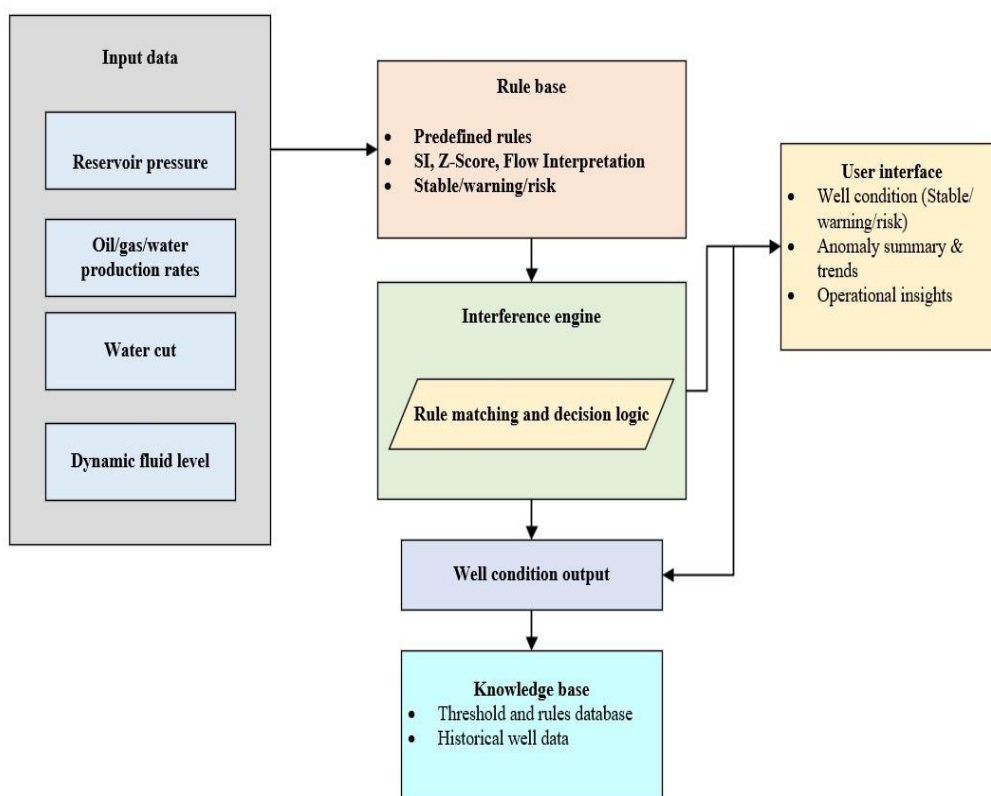


Figure 2. Architecture diagram of the rule-based classifier.

4. Results and discussion

This section includes a detailed discussion of the implementation of the proposed post-pressure monitoring and evaluation framework on a horizontal oil well (Well No. 807). The results are presented sequentially as per the evolution of pressure, behavior of pressure derivative (dp/dt), stability behavior, occurrence of anomalies, and well condition classification. The results of quantitative calculations are understood in terms of reservoir dynamics and wellbore behavior, as well as the implications they have on operations to indicate the usefulness of the suggested methodology and its practical applicability. The selected starting point aligns with the end of significant transient pressure variations observed in the dataset. Beyond this point, the pressure profile demonstrates a smoother and more consistent trend, indicating reduced influence of operational disturbances. This ensures that the subsequent analysis reflects the stabilization phase of the well. Minor variations in the selection of the starting point do not result in significant changes in the classification outcomes. The relative distribution of *stable*, *warning*, and *risk* states remains consistent under small shifts in the segmentation boundary, indicating that the framework maintains robustness with respect to the definition of the post-pressure stage.

4.1. Pressure trend analysis

Figure 3 shows the time-dependent change of the reservoir pressure throughout the post-pressure monitoring phase. Crude pressure data show short-term changes with amplitudes between 2 and 3 atm, which are mainly due to operational disturbances and sensor noise. Following the preprocessing and

smoothing phase, the pressure signal shows an understandable and vivid trend. In numbers, the pressure in the reservoir reduces by approximately 200 atm at the onset of the monitoring period to approximately 150 atm at the end of every 100 days, which is equivalent to a depletion rate of 0.5 atm/day. The first post-pressure period (0–30 days) is characterized by moderate oscillations around the smoothed trend, which is associated with the redistribution of the fluid along the horizontal wellbore and the equilibration of the pressure between the reservoir and wellbore system. In addition to this step, pressure declining is more stable and consistent. Significantly, there are no sudden pressure drops and continuous oscillations during the time of monitoring. This suggests that wellbore integrity and reservoir connectivity remain stable following pressure-related operations, even after pressure-reliant procedures. The findings ensure that the preprocessing and smoothing methods are effective in suppressing noise and retaining meaningful reservoir behavior, which can be used to support additional diagnostic analysis. Table 4 shows the summary of pressure trend statistics.

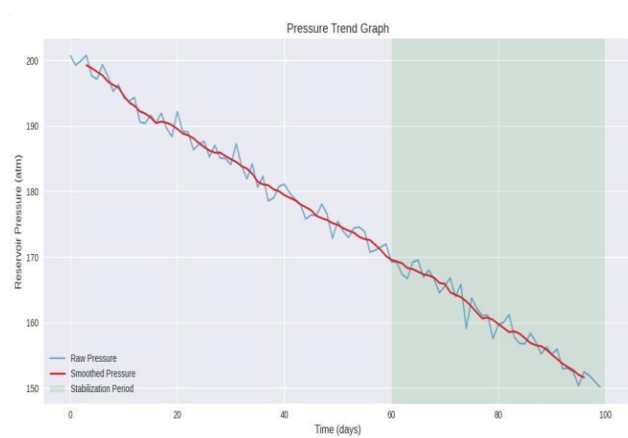


Figure 3. Post-pressure reservoir pressure trend.

Table 4. Summary of pressure trend statistics.

Parameter	Value
Initial pressure (atm)	~200
Final pressure (atm)	~150
Average depletion rate (atm/day)	~0.5
Maximum short-term fluctuation (atm)	±3

4.2. Pressure derivative (dP/dt) analysis

The results of the pressure derivative (dP/dt) are given in Figure 4, which depicts the time derivative of the first order of the reservoir pressure. The calculated values of pressure derivative (dP/dt) are mainly within the range of -0.05 to +0.05 atm/day, which means that the pressure remains stable during most of the post-pressure period. Nevertheless, there are a few local peaks, and the gradient magnitudes have their highest points at approximately ± 0.15 atm/day. The spikes are especially high during the early post-pressure period and are associated with abrupt changes of pressure in comparison with the current trend. These gradient excursions are seen as temporary flow

perturbations, which may be occasioned by local inflow variations, temporary blockages, pump adjustments, or temporary heterogeneities in the reservoir. Interestingly, the rate and intensity of gradient spikes become much lower during the later stages of monitoring, which indicates better pressure balance and constant flow conditions. Table 5 shows that the pressure derivative (dP/dt) analysis is an effective and sensitive tool to capture short-term dynamic behavior that might otherwise be unseen by looking at pressure trends.

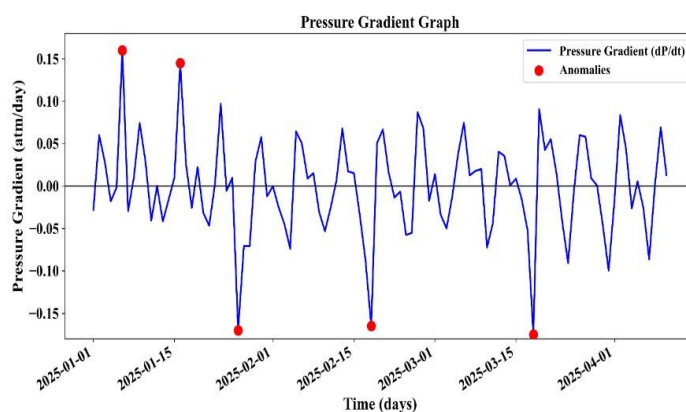


Figure 4. Pressure derivative (dP/dt) and anomaly detection.

Table 5. Pressure derivative (dP/dt) characteristics.

Metric	Value
Mean gradient (atm/day)	~0
Typical gradient range (atm/day)	−0.05 to 0.05
Maximum observed gradient (atm/day)	±0.15
High-gradient events	Isolated, short-lived

4.3. Stability evaluation

Figure 5 shows the rolling variance and stability index calculated using a moving window at the post-pressure stage. Quantitatively, the rolling variance values lie between 0.15 and 0.27 atm^2 , whereby it is higher in the initial monitoring period. In the initial 30–40 days, a high rolling variance denotes turbulent or transitional pressure behavior, as soon as pressure-related operations have been undertaken. With time, the rolling variance falls and becomes constant at 0.18–0.20 atm^2 , which represents a quasi-stable pressure balance. The monitoring period is divided into three stability regimes, based on predetermined stability levels (unstable, transitional, and stable). The steady regime is prevalent in the second half of the monitoring window, which proves the effectiveness of the pressure stabilization. This stability measurement is quantitative and gives an objective view of the system equilibrium, aiding in the interpretation and categorization of the anomalies (Table 6).

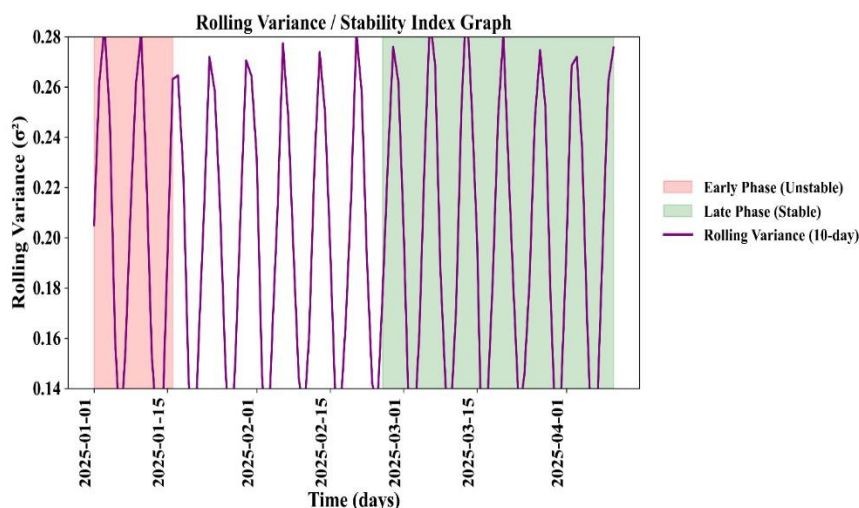


Figure 5. Rolling variance and Stability Index analysis.

Table 6. Stability Index summary.

Stability zone	Rolling variance range (atm^2)	Duration (%)
Unstable	>0.25	~ 20
Transitional	$0.20\text{--}0.25$	~ 30
Stable	<0.20	~ 50

4.4. Anomaly detection results

Figure 6 demonstrates the obtained results of anomaly detection based on the Z-score method. When the standardized Z-score is more than the $\pm 2\sigma$, pressure anomalies are detected. Mathematically, less than 8% of all pressure measurements are considered anomalies. These anomalies are sudden decreases or increases in pressure compared to the average pressure curve. The identified events are discrete and mostly coincide with an increase in pressure derivative (dP/dt) and rolling variance. This similarity confirms the strength of the multi-stage analytical framework. Notably, no long periods of abnormalities are visible, which means that there is no long-term deviant behavioral pattern. The infrequent occurrence and moderate intensity of abnormalities are indicative of small-scale disruptions in operations and not a severe wellbore breakdown. The Z-score approach, therefore, offers a valid and understandable process of early anomaly detection with field data that can be easily obtained (Table 7).

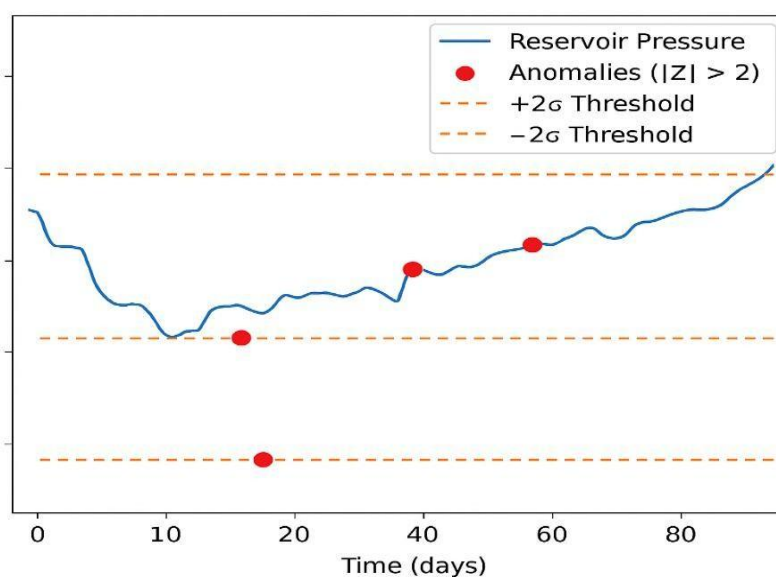


Figure 6. Statistical anomaly detection of post-pressure reservoir pressure using the Z-score method.

Table 7. Anomaly detection statistics.

Parameter	Value
Z-score threshold	$\pm 3\sigma$
Percentage of anomalous points	$\sim 8\%$
Nature of anomalies	Isolated, short-duration
Associated conditions	Gradient spikes, elevated variance

4.5. Well condition classification results

Final results of well condition classification are presented in Figure 7. Based on the suggested rule-based decision framework, there are *stable*, *warning*, and *risk* operational states of the post-pressure monitoring period. Quantitatively, 65% of the time of monitoring falls under *stable*, meaning a stable pressure balance and normal flow dynamics. Approximately 25% is classified under *warning*, which is usually related to moderate gradient variations or isolated anomalies. The portion of the time identified as *risk* is only 10%, relating to brief periods of high instability or recurrent abnormalities. This distribution proves that the well is mostly operating under stable conditions after pressure-related operations.

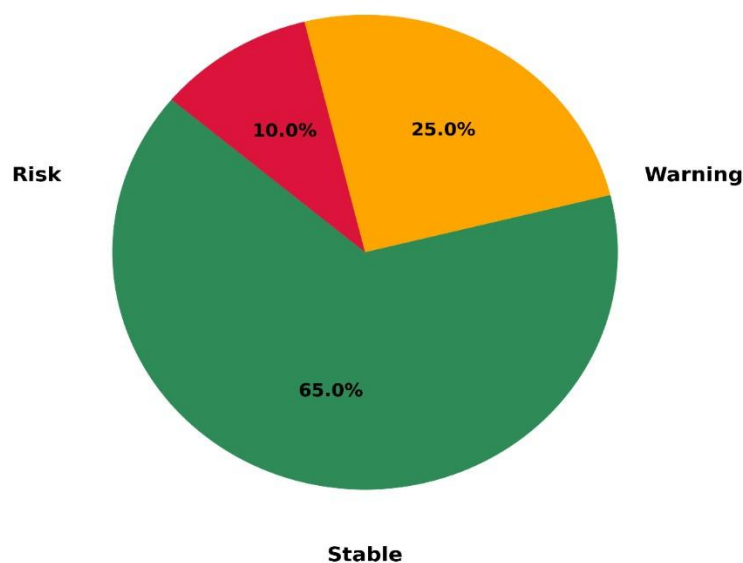


Figure 7. Well condition classification results.

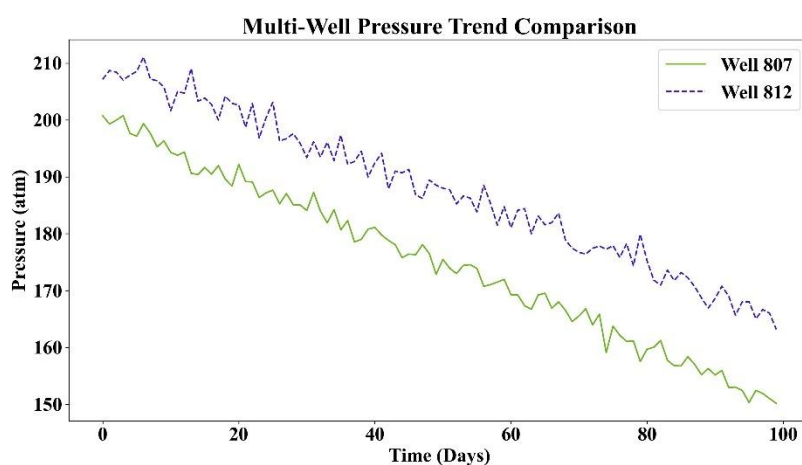


Figure 8. Pressure trend comparison for Well 807 and Well 812 over a 100-day period.

Figure 8 presents a comparison of pressure trends over time for two wells, Well 807 and Well 812. The graph shows the pressure (in atm) on the vertical axis and time (in days) on the horizontal axis. Well 807, represented by the green solid line, exhibits a steady decline in pressure over the 100-day period. In contrast, Well 812, depicted by the blue dashed line, shows a similar downward trend but with some variations in its pressure changes. Both wells indicate a gradual decrease in pressure, providing insight into their respective performance over the observed period.

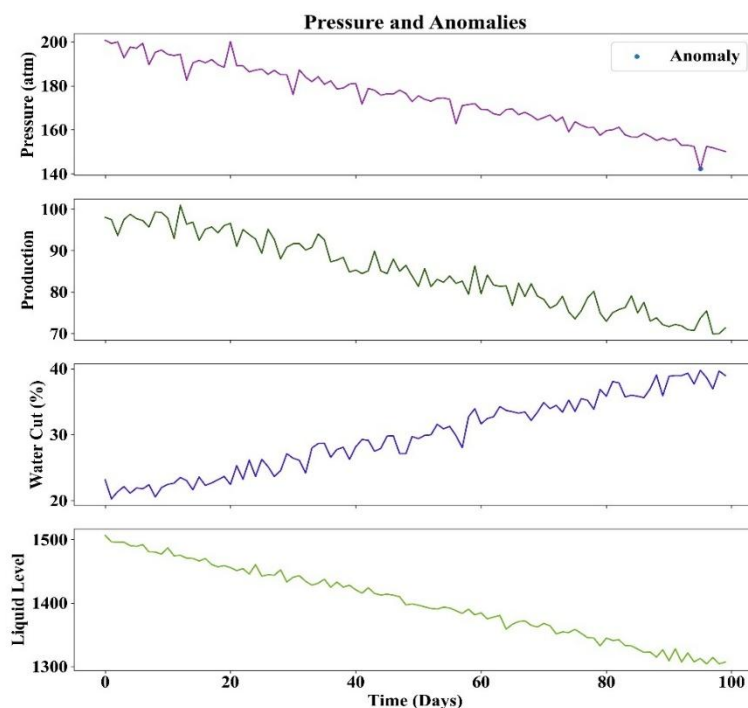


Figure 9. Pressure and anomalies.

Figure 9 illustrates multiple performance metrics related to a well, including pressure, production, water cut, and liquid level over a 100-day period. The topmost plot shows a gradual decline in pressure (in atm) over time, represented by the purple line. Below, the production levels (in percentage) also decrease, shown by the green line. The third plot highlights an increasing trend in the water cut percentage over the same period, represented by the blue line. Lastly, the liquid level (in arbitrary units) also decreases steadily, as shown in the green line at the bottom. Notably, anomalies are marked as blue dots across these plots. The rule-based classification is quite useful in converting intricate metrics of pressure-derived information into definite and operational field engineer insights (Table 8).

Table 8. Well condition classification summary.

Condition	Percentage (%)	Operational interpretation
Stable	65	Normal operation
Warning	25	Increased monitoring required
Risk	10	Potential intervention needed

Table 9 outlines the behavior of various parameters during anomalies and their physical interpretation. It highlights how fluctuations in production rate, water cut, liquid level, pressure gradient, and rolling variance provide insights into well performance. Short-term fluctuations in the production rate indicate transient flow instability, while a temporary increase in water cut suggests water breakthrough or channeling effects. Rapid variations in liquid level reflect fluid redistribution, and sharp spikes in the pressure gradient represent sudden pressure disturbances. Lastly, increased rolling variance values point to an unstable pressure regime, all of which are crucial for understanding well dynamics during anomalies.

Table 9. Parameter behavior and physical interpretation during anomalies.

Parameter	Behavior during anomalies	Physical interpretation
Production rate	Short-term fluctuations	Indicates transient flow instability in the wellbore
Water cut	Temporary increase	Suggests water breakthrough or channeling effects
Liquid level	Rapid short-term variation	Reflects fluid redistribution within the well
Pressure gradient	Sharp spikes	Represents sudden pressure disturbances
Rolling variance	Increased values	Indicates unstable pressure regime

4.6. Discussion and operational implications

The combined outcomes validate the efficacy of the suggested post-pressure assessment framework in both embodying long-term reservoir conduct and transient dynamic commotion with the help of standard pressure information. The rule-based methodology is easier to interpret and reproducible, providing as much transparency as data-intensive machine learning approaches, which is necessary in the field. The numerical data show that Well No. 807 can stabilize the pressure under a rather short post-pressure time interval, and transient disturbances are limited. The study suggests that future integration of visual imaging logging could further enhance the interpretation of pressure anomalies and diagnostic confidence by facilitating focused visual assessment of possible errors in the wellbore. On the whole, the results indicate that a trustworthy assessment of the post-pressure well can be implemented based on the combined efforts of pressure trend analysis, gradient diagnostics, stability measurements, and rule-based classification. The proposed framework can be scaled and extended to multi-well developments and assist in enhanced decision-making of operations, optimization of production, and risk management in a horizontal well setting.

5. Conclusion and future work

5.1. Conclusion

This research provided an interpretable and systematic post-pressure monitoring and evaluation system of horizontal wells, intended to enhance well condition determination after pressure-associated activities. This research offers an innovative solution for enhancing well stability, supporting sustainable energy and environmental goals. The proposed methodology offers a holistic and practical way of carrying out post-pressure diagnostics through the incorporation of pressure trend analysis, assessment of pressure derivative (dP/dt), stability analysis by use of a rolling variance, statistical anomaly analysis, and use of rules to classify well conditions. The proposed framework contributes to sustainable energy and environmental solutions by improving horizontal well monitoring, optimizing resource utilization, reducing operational risks, and supporting efficient well management. The framework emphasizes physical interpretability, transparency, and reproducibility through the integration of pressure trend analysis, pressure derivative analysis, stability evaluation, anomaly detection, and rule-based classification. Application to Well No. 807 demonstrated the ability of the framework to characterize post-pressure behavior and identify *stable*, *warning*, and *risk* operating conditions based on pressure-derived indicators. The results showed that approximately 65% of the monitoring period was classified as *stable*, 25% as *warning*, and 10% as *risk*, with detected anomalies being infrequent and short in duration. These findings indicate that the proposed framework provides

a structured and interpretable approach for post-pressure evaluation of the analyzed well. Further validation using additional wells and field conditions is required before broader deployment and generalization can be established.

5.2. Future work

Although the suggested framework exhibits good performance when the sampled data is the actual post-pressure field data, there are a number of research directions that can be applied in the future to improve the applicability and effectiveness of the framework. First, the use of real ultrawide-angle visual imaging logging information can be introduced in order to confirm the suggested pressure-imaging correlation quantitatively and enhance the process of anomaly interpretation. Second, the framework could be expanded to multi-well and multifield datasets to allow large-scale validation and evaluation of spatial variations under varying conditions of reservoirs. Moreover, the framework could be investigated based on adaptive thresholding and hybrid algorithms with lightweight machine learning models to enhance the sensitivity of anomaly detection under a highly dynamic operating regime. Another potential future use, which is also an option in the short term, is the real-time application of the framework to digital oilfield platforms, which will allow them to constantly monitor post-pressure and early warnings. Lastly, other parameters like flow rate, water cut, and temperature would also contribute to the enhancement of the evaluation framework and result in a multi-physics, post-pressure monitoring system, highly integrated to form an advanced horizontal well management system. Future work will incorporate ultrawide-angle visual imaging logging data for validation and improved interpretation of pressure anomalies.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The author declares that there are no known competing financial or personal interests that could have appeared to influence the work reported in this paper.

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