Petroleum Science 23 (2026) 7187–7206

Contents lists available at ScienceDirect

Petroleum Science

journal homepage: www.keaipublishing.com/en/journals/petroleum-science

Review Paper

Machine learning for gas kick detection in deepwater drilling: A review with multi-source data fusion

Qi-Shuai Yin [a,b,c,*], Zhi-Ming Yin [b,d], Zheng-Qiang Xu [b,d], Meng-Bo Li [d], Lai-Bin Zhang [b,c], Jin Yang [b], Dan Sui [e], Ying-Ying Guo [f]

[a] Hainan Research Institute, China University of Petroleum (Beijing), Sanya, 572000, Hainan, China
[b] College of Safety and Ocean Engineering, China University of Petroleum (Beijing), Beijing, 102249, China
[c] Key Laboratory of Oil and Gas Safety and Emergency Technology, Ministry of Emergency Management, Beijing, 102249, China
[d] CNOOC Research Institute Ltd., Beijing, 100028, China
[e] University of Stavanger, Kjell Arholms Gate 41, Stavanger, 4021, Norway
[f] Louisiana State University, Baton Rouge, LA, 70803, USA

ARTICLE INFO

Article history:
Received 23 April 2025
Received in revised form
9 March 2026
Accepted 6 June 2026
Available online 11 June 2026

Edited by Jia-Jia Fei

Keywords:
Deepwater drilling
Gas kick detection
Machine learning
Multi-source fusion
Early warning

ABSTRACT

Gas kick early warning in deepwater drilling is challenged by weak precursors and multi-source noise, which can delay detection and increase false alarms under conventional single-signal thresholds. This narrative review synthesizes recent advances in gas kick early warning methods based on machine learning and organizes the evidence with a decision-oriented framework that links sensing observability, feature construction, model design, evaluation metrics, and well control actions. Three themes recur: multi-source fusion across surface, riser, and downhole channels; a shift from shallow statistical learners to deep and hybrid architectures; and increasing emphasis on estimating influx volume and rate within operational workflows. Engineering evidence indicates that a developing gas influx produces distributed, time-shifted signatures along the wellbore that may emerge first in downhole, riser, or surface measurements depending on circulation and operating conditions. These considerations motivate an integrated monitoring layout that combines topside mud logging streams, riser acoustics, and annular pressure while drilling (APWD) or other while-drilling measurements. This review clarifies how monitoring outputs can be integrated into managed pressure drilling workflows to close the loop from detection and tiered alerts to operational adjustments. An illustrative offshore test case is included solely to demonstrate reporting schema and deployment context; the reported trial demonstrated a reproducible lead time of at least 12 min relative to conventional mud-logging surveillance. Overall, the review provides comparative, evidence-based, and deployment-oriented guidance to support earlier and more reliable gas kick early warning in deepwater operations.
© 2026 Publishing services by Elsevier B.V. on behalf of KeAi Communications Co. Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

1. Introduction

1.1. Background and problem definition

Early and accurate gas kick identification is central to well control in deepwater drilling. Deepwater operations face narrow operational pressure windows, highly variable marine conditions, and complex geology, which together increase loss-of-well-control risk and complicate operational decision-making (Fraser et al., 2014). A gas kick occurs when formation fluids enter the wellbore under an unfavorable pressure balance and migrate uphole. If not detected and controlled promptly, a kick may escalate into a blowout with severe economic, environmental, and human consequences; the Deepwater Horizon disaster remains a stark reminder (Stewart et al., 2022).

Deepwater environments further impede timely diagnosis. Long risers and mud compressibility introduce propagation delay and waveform dispersion between bottom-hole disturbances and surface measurements. Surface measurements are further contaminated by sea state and operational noise, while downhole pressure telemetry is bandwidth-limited and reliability constrained, yielding low overall signal-to-noise ratios (Maus et al.,

* Corresponding author.
E-mail address: yinqs@cup.edu.cn (Q.-S. Yin).
Peer review under the responsibility of China University of Petroleum (Beijing).

https://doi.org/10.1016/j.petsci.2026.06.012
1995-8226/© 2026 Publishing services by Elsevier B.V. on behalf of KeAi Communications Co. Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

1979; Li et al., 2022a). Early kick signals often appear as small-amplitude, short-duration perturbations, and gas expansion typically becomes pronounced only after the influx reaches the middle to upper wellbore, by which time pressure control can be too late to be fully effective (Sleiti et al., 2020; Zhang et al., 2025a; Molaei et al., 2023). As a result, fixed-threshold methods based on a single measurement point are prone to delayed detection and false alarms, motivating data-driven monitoring for earlier warning (Krishna et al., 2020).

Multi-source monitoring provides complementary value but requires unified calibration and fusion to be effective. Surface logs offer high sampling rates yet are noise-prone; riser measurements lie closer to the upward migration path but exhibit complex acoustic and hydraulic interference; downhole sensors provide strong physical indicators but are limited by telemetry constraints (Xu et al., 2019; Yin et al., 2020b; Tost et al., 2020; Zhou et al., 2021). When measurements from the surface, riser, and downhole domains are time aligned and their features are made comparable, cross-channel consistency can suppress noise while retaining sensitivity to minute-scale trends, which supports more reliable kick warning and decision support (Fan et al., 2020; Yin et al., 2021a).

Rare event frequency and coupled causality introduce additional requirements for modeling and evaluation. Under high-reliability operations, gas kicks are low-incidence events with severe class imbalance, and rig rhythms and control adjustments can introduce long temporal dependencies and concept drift (Osarogiagbon et al., 2021). Accordingly, models are commonly expected to capture long-horizon context and to balance missed and false alarms through calibrated thresholds. Kicks are driven jointly by bottom-hole pressure differential, mud properties, riser fluid structure interactions, and operational actions, with pronounced nonlinearity and interactions; therefore, actionable warning benefits from stable composite features, interpretable evidence for operators, and safeguards for cross-scenario robustness (Zhou et al., 2021; Pournazari et al., 2015). Within this context, machine learning has been increasingly adopted to integrate weak signals across channels and to support earlier warning, while remaining compatible with well control procedures and decision-making (Krishna et al., 2020; Sircar et al., 2021).

As a narrative review, this study synthesizes surface, riser, and downhole monitoring and their integration with machine learning and data fusion, benchmarks evidence against common baselines, and uses an illustrative case to clarify reporting and interpretation before summarizing challenges and a roadmap for deployment (Yin et al., 2021a, 2025).

Fig. 1 summarizes the evolution from manual and threshold-based detection toward real-time multi-source monitoring with fusion and machine learning, and it highlights why weak precursors and time-shifted measurements can limit fixed thresholds and motivate standardized reporting for early warning and influx quantification.

1.2. Methodology of the review

Gas kick early warning in deepwater drilling involves a transient influx process driven by bottom-hole pressure imbalance and multiphase behavior. Relevant signatures are observed through surface, riser, and downhole measurements that differ in delay, noise level, and reliability (Jiang et al., 2020). To compare heterogeneous technical routes within a common problem space, the evidence is organized as a five-step pipeline that links monitoring to operational response. The pipeline proceeds from operational measurements to feature representations to modeling paradigms to evaluation metrics and finally to well control decisions, with each step stated explicitly in items (i)–(v).

(i) Operational measurements. The review compiles raw measurements describing wellbore mechanics and boundary conditions, for example, rate of penetration, bottom-hole pressure, acoustic amplitude, and differential flow out, alongside other routinely reported surface, riser, and downhole signals (Sircar et al., 2021).

(ii) Feature representations. Studies are compared based on their feature construction from raw measurements, including time domain statistics, frequency domain indicators, time frequency representations, and sliding window descriptors of trends and changes (Tang et al., 2019; Sun et al., 2018; Wang et al., 2023a).

(iii) Modeling paradigms. Approaches are grouped into threshold and mechanistic models; probabilistic and state estimation methods such as Kalman filter variants; conventional supervised learning models such as support vector machine (SVM) and gradient boosting decision tree (GBDT); deep learning models designed for long temporal dependencies such as long short-term memory (LSTM), convolutional neural network (CNN) coupled with LSTM, and attention mechanisms; and physics constrained hybrids with multi source data fusion (Zhu et al., 2024; Pandey et al., 2020; Zhang and Samuel, 2024).

(iv) Evaluation metrics. Warning lead time (Δt) is defined as the interval between the onset of gas influx and the first reliable detection or alarm, indicating how early the system can provide an actionable warning before escalation. Accuracy and receiver operating characteristic (ROC) based metrics are extracted when reported, together with false positive rate and false negative rate, where available. For studies that estimate influx size or rate, regression error metrics are recorded.

(v) Well control decisions. The review compares how model outputs are operationalized, through threshold calibration and cost trade-offs, into alarms and actions used in well control practice. Examples include managed pressure drilling (MPD) pressure management, choke programs, and shut-in strategies, together with their linkage to barriers such as the blowout preventer (BOP).

This narrative review focuses on gas kick monitoring and early warning in deepwater and ultra-deepwater drilling, with emphasis on integrating surface, riser, and downhole measurements with machine learning and multi-source fusion. Table 1 summarizes representative studies that pursue either classification warning or quantitative prediction under different data and models, reflecting differentiated strategies to improve monitoring accuracy while extending warning lead time under noisy, time-shifted measurements. Sections 2 and 3 synthesize monitoring technologies and machine-learning workflows, and Section 4 presents an offshore test-oriented illustrative case showing practical application.

2. Development and applications of gas kick monitoring technology

Gas kicks are a primary precursor to blowouts in deepwater drilling, so early detection and timely intervention are decisive for safe and efficient operations. Recent practice has moved from passive checks to predictive monitoring built on clearer physics, better sensing, and data-driven inference (Muojeke et al., 2020). Table 2 organizes the monitoring landscape by channel—surface,

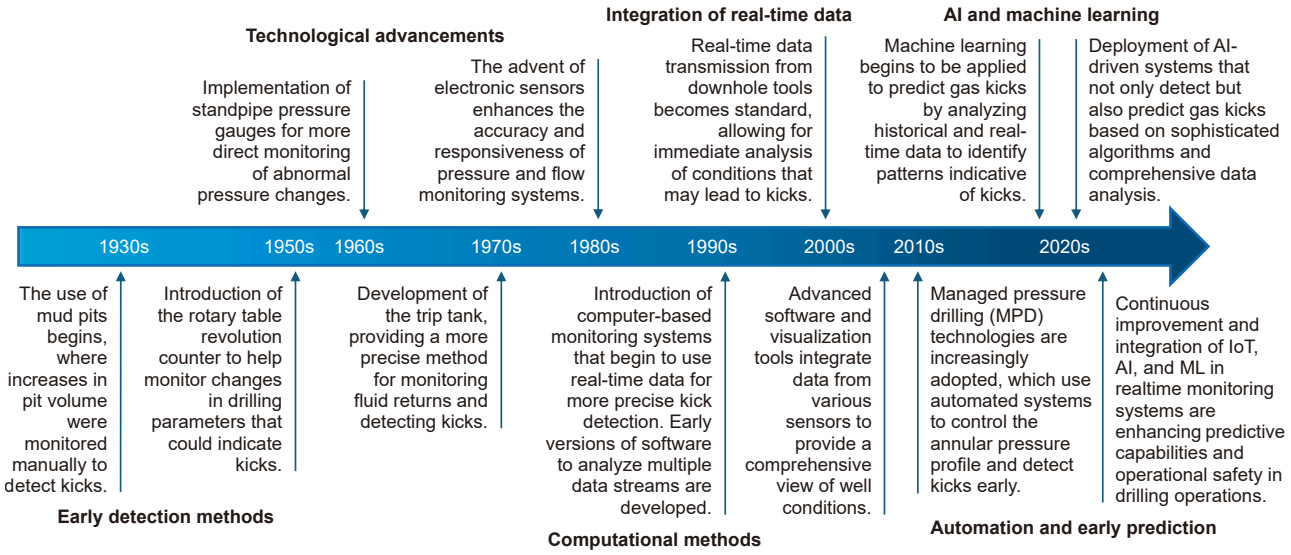


Fig. 1. Milestones in gas kick detection from conventional thresholds to multi-source fusion.

Table 1
Research on the application of machine learning in deepwater gas kick detection.

References	Data provenance	Monitoring inputs	Model task and route	Reported model effect	Key boundary noted
Sun et al. (2018)	Simulation anchored with a field-well demonstration	Return flow; pit gain; standpipe pressure; rate of penetration (ROP)	Pattern recognition with probability diagnosis using mode matching and weighted fusion; weights determined by analytic hierarchy process (AHP)	Overflow sensitivity based on pit gain reaches 0.177 m^3	Case-level evidence; depends on mode extraction and weighting strategy
Fjetland et al. (2019)	OpenLab high-fidelity drilling simulator baseline	Flow rate in; flow rate out; standpipe pressure; choke pressure; choke opening; bit pressure; bit depth	Long short-term memory recurrent neural network (LSTM-RNN) for detection and influx-rate estimation	Test-set classification accuracy 93.5%–97.4%; test-set influx mass-rate root mean square error (RMSE) 0.10 kg/s	Simulator domain assumptions; transfer to field requires accounting for noise and operational variability
Xu et al. (2023)	Surface monitoring time-series example	Flow differential data; mud pool increment data; pressure data; rate of penetration (ROP); prior probabilities for state, pump on, and loss events assumed	Pattern recognition for kick detection with probabilistic diagnosis	Under noise amplitude of 16 L/s, the model detects continuous overflow about 200 s after the true overflow occurs	Sensitivity to noise and prior probability settings; motivates multi-signal fusion and threshold calibration
Wang et al. (2023b)	Deepwater field mud-logging data, South China Sea	Drilling and mud-logging parameters distinguishing fast engineering signals and slow mud-property signals	Ensemble learning for kick classification with continuous-point labeling option	Continuous-point labeling recommends a continuous positive length (Lc) of 5 m with average comprehensive error 5.48%; single-point labeling yields an average comprehensive error of 8.02%	Labeling strategy and Lc selection affect performance; slow mud properties introduce lag
Li et al. (2025)	Laboratory drilling system experiments; two datasets labeled SDS and LDS	Differential flow (DF); bottomhole pressure (BHP); conductivity of drilling fluid (CDF); density of drilling fluid (DDF); LDS also records torque, rotary speed (RPM), weight on bit (WOB), and gas pressure (GP)	Comparative machine learning models; best reported for SVM with linear kernel (SVM-linear)	Test accuracy 0.968 for SVM-linear; missed alarm rate 0.06; false alarm rate 0.11; lag time 1.3 s; comprehensive equivalent time 23.13 s	Experimental domain; performance depends on feature set consistency across datasets
Zhang et al. (2026)	Pilot-scale deepwater gas kick monitoring experiment; ultrasonic riser monitoring	One-dimensional acoustic reception signals collected by ultrasonic transducers mounted on the riser	Multiscale fuzzy diversity entropy (MFDE) feature extraction with SVM; gas-content identification and quantitative inversion	MFDE–SVM achieves average identification accuracy over 96.2% across liquid-phase flow rates and gas-content operating conditions	Scope limited to tested operating conditions; additional factors such as fluid viscosity and solids are discussed as future verification needs

Table 2
Gas kick monitoring technologies in deepwater drilling.

Detection technique	Basic principle	Applicable operating conditions	Typical signal	Key advantage	Key limitation
Pit volume monitoring	Track pit volume increase as an indication of influx entering the wellbore	Best under stable circulation and disciplined pit management; confounded by frequent topping-up and pump transitions	Pit level or pit volume trend	Simple and robust, provides intuitive evidence of an influx event	Slow response and non-specific, since volume changes can also arise from operations or surface issues
Flow rate monitoring	Compare flow in and flow out to detect flow imbalance associated with influx	Requires well-calibrated flowmeters and stable flow paths; interpretation should mask connection and pump transition periods	Differential flow between inlet and return	Real-time monitoring enables quantitative imbalance estimation and faster operator awareness	Highly sensitive to instrument calibration and operational transients, which can drive false alarms
Standpipe pressure monitoring	Monitor standpipe pressure deviations that accompany changes in circulating system behavior	Requires reliable pressure sensing and consistent interpretation under varying operations and sea states	Standpipe pressure trend and transient response	Fast feedback to sudden hydraulic changes, widely available on rigs	Pressure fluctuations are not unique to kicks and require discrimination from normal operational changes
Acoustic sensing (riser or string instrumentation)	Detect changes in acoustic propagation caused by gas presence and multiphase flow	More demanding installation and calibration; most effective when the signal-to-noise ratio is adequate	Acoustic amplitude, velocity, or spectral change indicators	Sensitive to small influx under favorable conditions, offering earlier physical cues in some cases	Higher cost and analysis complexity; performance depends strongly on installation and operating envelope
Real-time downhole pressure and temperature monitoring	Use downhole sensors to capture anomalies near the source and transmit them to surface	Requires stable telemetry and robust sensors; attenuation and data gaps must be managed	Downhole pressure and temperature time series	Physically close to the influx source and can provide early, interpretable changes	High cost and technical complexity; telemetry limits and sensor failures can introduce gaps or delays
Integrated multi-domain monitoring (surface–riser–downhole)	Combine complementary cues across domains and reconcile them for decision support	Requires compatible interfaces, time synchronization, and clear alarm-to-action mapping	Cross-domain consistency of flow, pressure, and acoustic cues	Improves reliability by reducing single-signal ambiguity and enabling tiered warning logic	Integration and calibration are non-trivial and require engineering governance to avoid conflicting indications

riser, and downhole—and summarizes what each can see, which mechanisms govern the signals, and how quickly and cleanly those signals arrive. Surface measurements track flow and density changes with high sampling but low signal-to-noise under rig activity. Riser measurements follow the migration path yet are affected by acoustic and hydraulic interference and by transmission delay. Downhole measurements, including annular pressure while drilling, provide strong physical indicators but are limited by telemetry and calibration drift. These contrasts highlight complementary observability across domains, while also clarifying the integration prerequisites and failure modes that must be addressed for a practical combined monitoring scheme.

2.1. Experimental simulations and numerical models

At the laboratory level, simulation devices and numerical models have been developed to replicate the dangerous conditions associated with gas kicks. This replicates gas kick phenomena under controlled conditions and supports the evaluation of detection technologies. However, machine learning models require large and high-quality datasets to achieve high-precision results, and the primary challenge lies in obtaining such data (Osarogiagbon et al., 2021).

Experimental simulation research initially focused on high-fidelity experimental devices to replicate gas kick events, measuring variations in key parameters. Meng et al. (2015) combined numerical simulation and laboratory experiments to investigate transient gas–liquid flow behavior during gas kick/injection. Using a drift-flux model coupled with the Shi slip relation, they reproduced annular pressure responses and demonstrated the influence of gas flow rate, liquid flow rate, and well depth on bottom-hole pressure variation.

As experimental conditions became more complex, researchers increasingly relied on a combination of numerical models and experimental simulations to better understand and predict outcomes. Wang et al. (2016) introduced the water hammer effect to develop a mathematical model for pressure changes during gas kicks. Their findings showed that an early warning could be triggered when the gas influx volume reached 0.5–0.8 m^3, enabling earlier detection than traditional methods. Similarly, Yang et al. (2019a) developed a gas kick detection method and verified its efficiency and low false-positive rate using experimental devices. The experimental data showed that this method could confirm a gas kick within 2–7 min, reducing response time.

In recent years, experimental platforms have evolved further to simulate drilling conditions across multiple scenarios. For instance, Sule et al. (2019) developed an experimental drilling platform that integrated surface monitoring with a gas injection platform. Their study found that gas kicks significantly reduced drill bit vibration amplitude, providing a potential early detection indicator. Additionally, Yin et al. (2020a) employed Doppler ultrasound to detect non-contact gas phase fractions and reported a strong correlation between Doppler frequency shifts and gas content. This method can reduce operational interruptions associated with drilling fluid disturbances, making it promising for practical applications.

Recently, research has gradually shifted toward intelligent and high-sensitivity detection methods. For example, Wang et al. (2024) proposed a low-frequency elastic wave detection method and, through numerical simulations and experimental analysis, demonstrated high sensitivity to gas kicks. Similarly, Fjetland's team (Fjetland et al., 2019) applied LSTM neural networks to analyze drilling data and generated multi-scenario datasets on the high-fidelity OpenLab simulator for model training. Despite rich

simulation data, the lack of field validation remains a bottleneck for practical applications.

Experimental simulations and numerical models have been central to gas kick prediction research. These studies support both mechanistic understanding and method development. However, gaps remain between laboratory studies and field conditions. Overcoming challenges such as transferring experimental insights to engineering practice, integrating multi-source data with intelligent algorithms, and adapting to variable environmental and operational conditions is essential. Further work is needed to develop experimental setups that better approximate field conditions and to validate models with field data.

2.2. On-site gas influx monitoring methods

Gas kick monitoring is critical for the safety and efficiency of deepwater drilling operations. In practice, monitoring technologies can be grouped into three categories: platform-based, riser-based, and downhole-based. Because these systems are deployed at different locations, they capture different stages of gas influx evolution and therefore provide different early-warning capabilities. In principle, downhole data can provide the earliest and most direct indication of gas kick risk, but practical deployment and rapid data transmission remain challenging.

Platform-based monitoring primarily relies on integrated mud-logging technologies, including conventional methods such as pit volume and flow-rate monitoring, as well as approaches using acoustic or pressure-wave signals and multi-parameter combinations to identify gas kicks. Early detection was largely based on basic fluid-dynamics principles, where wellhead flow measurements were relatively easy to implement and provided direct indications of abnormal influx. Integrated monitoring can help reduce noise and improve detection robustness, making it widely used in current field practice (Johnson et al., 2014). In recent years, companies and research institutions have improved sensor types, algorithms, and system stability, further enhancing monitoring precision (Osarogiagbon et al., 2021). A key limitation, however, is that platform-based monitoring often detects the event only after a noticeable influx has entered the wellbore, which can introduce delays and increase the risk of loss of well control (Maus et al., 1979).

Riser-based monitoring commonly uses standpipe-pressure surveillance and acoustic sensing (Sharma et al., 2020, 2021). Standpipe-pressure monitoring continuously tracks pressure in the drill string, where sudden deviations may indicate gas intrusion. Because these measurements are closer to the migration path than surface-only indicators, they can provide earlier warning in some conditions (Williams et al., 2020). Acoustic sensing can further enhance sensitivity by analyzing sound-wave propagation in the drilling fluid, since gas alters acoustic characteristics. These techniques can improve detection performance, but they also add cost and operational complexity and require careful calibration and interpretation.

Downhole-based monitoring relies on pressure while drilling (PWD) and logging while drilling (LWD) systems to track multiple parameters for early detection. Gas influx can change annular pressure and temperature and can alter drilling-fluid properties such as density and electrical conductivity. Accordingly, downhole monitoring may incorporate pressure, temperature, flow, acoustic, and fiber-optic sensors placed near the drill string and bit to capture downhole responses (Li et al., 2022b). Continuous sensing supports real-time anomaly detection and can provide timely signals for decision-making. However, these systems involve higher costs and integration complexity and depend on reliable telemetry, efficient data handling, and trained personnel.

Overall, the three domains are complementary. Integrating monitoring locations, parameters, and technologies into a coordinated workflow can combine their strengths, mitigate single-source limitations, and improve both timeliness and reliability for gas kick warning.

2.3. Multi-source early warning methods for gas kick detection

2.3.1. Machine learning for proactive kick detection

Deepwater and ultra-deepwater operations present unique challenges for gas kick detection because early signals can be weak and gas kick evolution can be rapid under these conditions. Traditional methods are often reactive, relying on post-event judgment or empirical threshold values, and are therefore prone to missing early signals when parameter fluctuations are subtle. Once a gas kick develops into a large pressure imbalance, intervention time can be limited. In contrast, machine learning methods can analyze historical and real-time data to identify early warning patterns and support proactive detection (Muojeke et al., 2020; de Oliveira Werneck et al., 2022). This shift can provide additional decision time for drilling engineers and improve the timeliness of response.

The advantages of machine learning in deepwater gas kick detection include nonlinear feature learning, multi-source data fusion, and adaptation to changing operating conditions. In particular, deep learning models can extract latent representations from multivariable time-series data, such as pressure, temperature, flow rate, and density (Feng et al., 2025), which can improve sensitivity to weak precursors. Online or incremental learning can further update model parameters as conditions change, helping maintain performance under operational variability. Moreover, integrating signals from the platform, riser, and downhole systems can improve robustness by reducing reliance on any single indicator.

Despite these advantages, practical deployment remains constrained by data quality, computational requirements, and integration with existing workflows. Ongoing research, therefore, focuses on data governance, model optimization, and deployment strategies to support field-ready early warning.

2.3.2. Integrated real-time monitoring system

Fig. 2 shows an integrated multi-source real-time monitoring system that combines surface, subsea, and downhole measurements within a single early-warning architecture (Yin et al., 2021a). The figure clarifies how drilling parameters, riser responses, and downhole measurements can be connected to machine-learning assessment, thereby forming a complete workflow from sensing and data transmission to feature extraction, model inference, and operational warning.

By integrating this early warning system, the completeness of drilling data is ensured, and real-time gas kick detection becomes more accurate and efficient. The system demonstrates high robustness and fault tolerance, effectively mitigating the risks posed by equipment failures or sensor signal loss.

Overall, deepwater gas kick monitoring is advancing toward a new technological phase characterized by multi-source integration, intelligence, and high reliability. Machine learning and advanced sensing technologies play a key role in this transition. Future research should explore the adaptability of data resources, algorithm deployment, and integration with engineering applications. Such research will lay a solid foundation for the broader adoption of these technologies across different well regions and platforms, enabling their effective and scalable deployment in the industry.

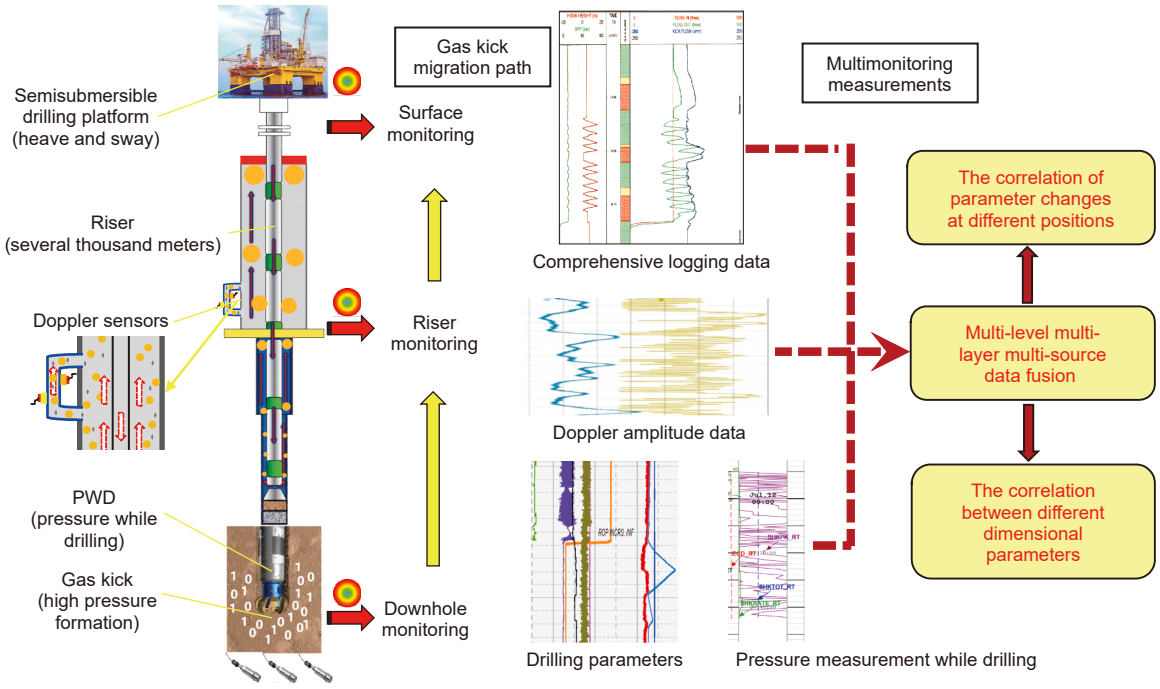


Fig. 2. Schematic of the novel gas-kick-detection method (Yin et al., 2021a).

3. Machine learning methodologies

Early detection of gas kicks increases the decision time available for well-control actions, especially when influx growth accelerates in the mid-to-upper wellbore. As a bridge from the study-level evidence summarized in Table 1 to model-specific workflows, Fig. 3 presents the typical machine-learning pipeline used for deepwater gas kick detection. The workflow begins with multi-source data acquisition and data cleaning, proceeds through feature engineering and sample construction, and then enters model training, model evaluation, and deployment. This structure is useful for comparing different algorithms because it makes the links among raw measurements, features, labels, performance metrics, and field decisions explicit.

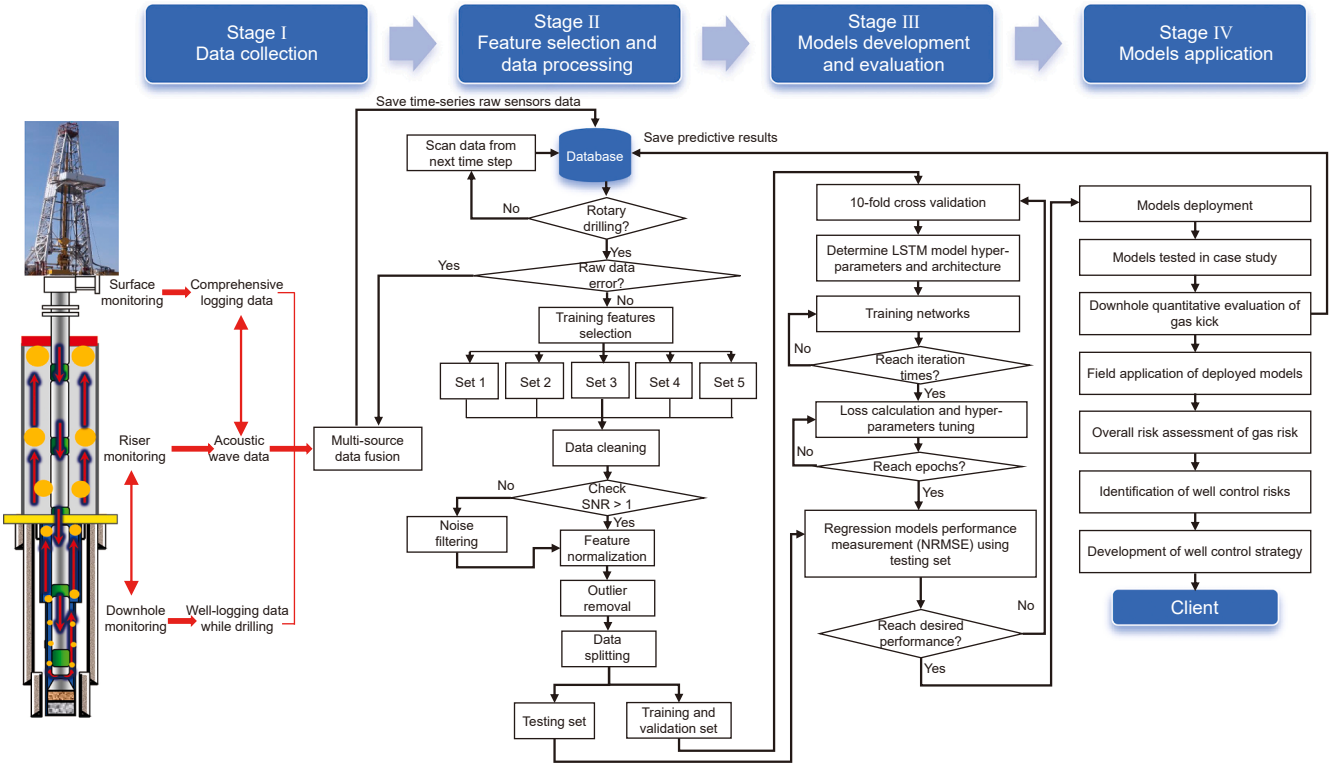


Fig. 3. Workflow for multi-source data fusion and LSTM-based gas kick detection in deepwater drilling (Yin et al., 2022).

3.1. Machine learning approaches in drilling risk monitoring

3.1.1. Review of machine learning progress in gas kick monitoring

Machine learning applications for gas kick monitoring have evolved significantly, transitioning from initial probabilistic inference models to complex deep learning and multi-model systems, supporting improved operational safety and efficiency. For instance, Hargreaves et al. (2001) introduced a Bayesian probabilistic framework to dynamically quantify uncertainties in critical parameters such as mud flow rate and pressure, maintaining high detection sensitivity despite noisy environments typical in deepwater conditions. Nybø et al. (2008) further enhanced monitoring accuracy by integrating physical models with echo state networks (ESN), effectively capturing nonlinear temporal features in drilling data and minimizing false alarms.

With increasing demand for real-time detection capabilities, Unrau et al. (2017) utilized decision trees and SVM to dynamically adjust well control thresholds, distinguishing normal from abnormal conditions and improving detection responsiveness. Addressing challenges of limited data availability, Borozdin et al. (2020) employed digital twin technologies combined with artificial neural networks (ANN), generating simulated training datasets to enhance predictive generalizability under diverse operational scenarios.

Recent advancements in deep learning methods, particularly LSTM networks, have improved gas kick prediction in deepwater scenarios. Yin et al. (2021b, 2023, 2025) reported LSTM and bidirectional long short-term memory (Bi-LSTM) models integrated with multi-point sensor data from downhole, riser, and surface monitoring systems, improving predictive accuracy and responsiveness. Similarly, Wang et al. (2023a) applied LSTM-based models to early gas kick detection using real-time drilling parameters, enabling timely interventions.

To address black-box concerns while preserving early-warning utility, recent studies embed interpretability at three points along the chain from monitoring to modeling to action. At the feature level, physics-anchored contributors—such as differential flow and density coupling, bottom-hole-pressure rate, and riser acoustic energy—are ranked and visualized over the decision window, and the attributions are aligned to a unified timeline across surface, riser, and downhole channels; this makes the 'acoustic-first, surface-later' chronology auditable and ties saliency to recognized precursors of gas ascent (Xu et al., 2019). At the decision layer, probability scores are paired with calibrated thresholds and explanations targeting confusion cases to manage the trade-off between warning lead time and missed alarms in well control contexts (Krishna et al., 2020). For operational handoff, alarms are generated from probability outputs using predefined thresholds and bypass logic after a two-stage MPD-oriented workflow that combines multivariate online change-point detection based on an elliptic envelope with a DNN event-type classifier (Gu et al., 2021).

To further improve model robustness, Obi et al. (2022, 2023) combined ANN, K-means clustering, and decision trees in a multi-algorithm fusion strategy, mitigating issues arising from noisy and sparse data distributions. Yang et al. (2019b) employed principal component analysis (PCA) in conjunction with ANN to streamline feature selection, enhancing computational efficiency and accuracy in real-time monitoring scenarios. Ifenaike and Oluwadare (2024) proposed a multi-layer prediction framework using logistic regression followed by Isolation Forest, managing false alarms and identifying potential high-risk events in safety-critical operations.

3.1.2. Applications of machine learning: insights and challenges

Despite progress, ML-driven gas kick detection faces ongoing challenges, including data quality control, model interpretability, and integration in operational environments. Noisy and incomplete data require rigorous preprocessing and simulation techniques to ensure accuracy. Real-world deployment demands robust edge computing solutions, necessitating systems capable of low-latency, fault-tolerant performance. The complexity of neural network architectures has also increased the importance of model interpretability, essential for operator trust and effective implementation.

Future research trends indicate growing integration of digital twin technologies with few-shot and transfer learning methodologies, leveraging simulation environments to address data scarcity. Transfer learning can support adaptation of models across varying operational contexts, reducing deployment costs and development timelines. Continued development in explainable artificial intelligence and advanced visualization techniques may further enhance operator trust and facilitate broader acceptance of intelligent monitoring systems.

In summary, machine learning applications in gas kick detection have transitioned from basic probabilistic methods to deep learning and integrated multi-model systems, improving detection sensitivity and operational response capability. Persistent challenges related to data quality, interpretability, and deployment can be addressed through emerging technologies such as digital twins, explainable artificial intelligence (XAI), and adaptive learning methods, supporting more reliable deepwater drilling operations.

3.2. Data processing

3.2.1. Data harmonization and quality control

Under deepwater conditions, surface, riser, and downhole channels exhibit long latency, high noise, and asynchronous telemetry. Without aligning data definitions and time bases, any estimate of warning lead time or false alarm rate will be biased. Early-warning bottlenecks have been linked to cross-channel inconsistency and surface-side delay. Subsequent work shows that riser pressure-difference and ultrasonic channels can be more sensitive to early upward migration, but timing errors can flatten weak precursors. Accordingly, this review defines comparable data through four constraints—calibration, time alignment, depth or state alignment, and gap/outlier handling—applied before feature engineering and modeling.

Zero-offset and gain drift can turn steady segments into pseudo-anomalies, while timestamp drift can attenuate true precursors into noise. In practice, zero and gain checks should be performed within known steady windows, with long-window drift monitoring in parallel. Cross-channel alignment can combine event tagging and cross-correlation, and residual lags should be verified against pump start–stop sequences. Online recalibration has been shown to suppress false alarms (Pournazari et al., 2015), and event-based alignment restores cross-channel consistency (Mills et al., 2012). The immediate benefits are unbiased warning-lead-time estimation, disappearance of steady-state-induced false positive rate (FPR) spikes, and improved cross-well reproducibility.

Because early kick signatures often appear as low-amplitude, short-duration perturbations, features should be extracted within state-consistent windows; otherwise, derivatives, slopes, and energy metrics will be overwhelmed by operational rhythms. Reliable feature extraction requires that all monitoring channels

be aligned to the driller's depth reference and corrected for drill-string stretch and stick-slip effects. Furthermore, only data acquired during steady circulation or continuous drilling should be retained for analysis, while surface and riser measurements should be resampled to a common cadence after lag compensation. Two-point bottom-hole pressure (BHP) consistency improves early discrimination (Yang et al., 2019a), and annular pressure while drilling (APWD) provides direct sensitivity to bottom-hole disturbances (Wang et al., 2016). These steps can reduce cross-well feature variability and improve the stability of decision thresholds across wells.

On the riser and acoustic side, construct energy, dominant frequency, bandwidth, and cross-channel amplitude ratios to capture spectral transitions associated with gas ascent. On the downhole side, differential flow and density coupling, the rate of change of equivalent circulating density (ECD), and pressure-recovery time constants can be constructed to reflect conservation laws and transient response (Zhang et al., 2025b). Cross-channel consistency and phase stability can then be used to identify the causal order described as "acoustic first, surface later". Sensitivity of acoustic and pressure-difference features has been documented (Xu et al., 2019). For feature selection and dimensionality reduction, prioritize interpretable quantities using mutual-information and spectral criteria. In practice, avoid high-dimensional "kitchen-sink" designs. Instead, a closed loop from physical hypothesis to features to metrics should be maintained so that each feature has a directional rationale for its effect on warning lead time (Δt), FPR, and false negative rate (FNR).

Samples should be formed using fixed-length sliding windows. Event onset should be defined according to the field rule of first sustained deviation and cross-checked against well control logs. Thresholds should be determined on the validation set and then kept fixed on the test set to avoid test set tuning. Time-ordered splits and fixed decision criteria are essential for credible early-warning assessment (Hargreaves et al., 2001). This determines auditability—whether readers can reproduce the same warning lead time and error rates.

Rare positives are the norm. Leakage risk should be controlled first through cost-sensitive learning and calibrated thresholds, followed by order-preserving under- or oversampling to balance batches. Generative augmentation should be used sparingly and only after distortion has been assessed (Aljubran et al., 2021). Multi-site collaboration can improve generalization while protecting data sovereignty through federated learning. For evaluation, both Δt and FNR should be reported to avoid high-accuracy yet high-miss-rate artifacts.

Time-ordered and leave-one-well-out protocols mitigate optimistic bias from overlapping windows on pilot and industrial datasets. For cross-basin transfer, domain-wise validation should be used, and in-domain and out-of-domain performance should be reported separately. Comparative reporting should include warning lead time, recall or accuracy, FPR, FNR, area under the receiver operating characteristic curve (AUC), inference latency, and computational load, together with sample size, split strategy, and threshold-selection method. Confidence intervals or significance tests are recommended for key metrics to ensure comparability (Zhou et al., 2021).

This subsection's workflow—calibration and time alignment; depth or state alignment; physics-anchored and multi-scale feature design; order-preserving sample formation with cost-sensitive imbalance handling; and time-ordered or leave-one-well-out benchmarking—directly targets three deepwater pain points: asynchronous channels, weak precursors, and sparse positives. Its immediate outcome is a comparable set of Δt and FPR/FNR estimates that serve as a common yardstick for the traditional-versus-ML comparison in Section 3 and the pilot and field cases in Section 4.

3.2.2. Feature extraction and sample formation

This subsection operationalizes the chain from physics to data to models to metrics. After cross-channel calibration, time alignment, and state alignment, multiscale features are constructed under physics priors across the time domain, the frequency domain, and joint time–frequency representations, together with mechanistic quantities. Redundancy control and dimensionality reduction then yield stable and interpretable inputs. Samples are formed with sliding windows and order-preserving labels; class imbalance is handled with cost-sensitive schemes and minimal augmentation. Finally, standardized evaluation with chronologically ordered splits or leave-one-well-out validation ensures that performance is verifiable, transferable, and deployable.

Data cleaning covers missing-value handling, outlier screening, and noise reduction to improve input quality for model training. When data scarcity is severe, augmentation should be used cautiously and only after verifying that perturbations do not distort physically meaningful trends. Cross-site learning can also be considered when data sharing is constrained, but the evaluation protocol should remain time-ordered and leakage-resistant.

Feature engineering strongly influences model effectiveness. Feature relevance can be screened using correlation measures and mutual-information criteria, and redundancy can be reduced with dimensionality-reduction methods such as PCA and linear discriminant analysis (LDA). Common feature candidates include outlet flow indicators, drilling-fluid density, temperature, electrical conductivity, hook load, rotary torque, drill-pipe pressure, and annular pressure losses.

Feature extraction typically leverages statistical measures (e.g., mean and standard deviation), time-domain trend descriptors, frequency-domain indicators, and time–frequency transforms to capture weak, transient perturbations (Keil et al., 2022). Recent work also discusses automated feature engineering and representation learning, including CNNs and LSTM networks, to reduce manual intervention (Verdonck et al., 2024). Attention mechanisms are often used to highlight time segments or variables with higher predictive contribution.

After feature construction, normalization, and data partitioning are required for fair assessment. Data should be split into training, validation, and testing subsets using time-ordered protocols. Sliding-window sampling is commonly used for time-series formation and is particularly important when kick events are short-lived, but overlap-induced leakage must be controlled (Aljubran et al., 2021).

In summary, data harmonization, disciplined feature design, and leakage-resistant validation form the technical basis for ML-based gas kick detection. The primary objective is not to maximize headline accuracy, but to produce results that remain interpretable, auditable, and stable under operational variability.

3.3. Gas kick classification and quantitative detection models

Deepwater operations impose dual requirements on warning lead time and robustness, motivating a shift from binary alarms to a parallel framework of tiered classification plus quantitative estimation. The classification branch provides actionable alarm levels, while the regression branch outputs influx volume and rate; together they interface with well control calculations and operating procedures. The evidence and comparisons below are organized under unified data definitions and validation protocols, avoiding redundant algorithm detail.

3.3.1. Tiered alarming: sequence classification for multi-source monitoring

Yin et al. (2021a) used combined surface, riser, and downhole monitoring as input and constructed multi-level risk labels to replace error-prone binary thresholds, evaluating generalization with chronologically ordered training, validation, and test splits. On a pilot-scale rig, a multi-layer LSTM model trained on key features—wellhead flow and pit volume, riser-base acoustic amplitude, bottom-hole pressure, and ECD—achieved approximately 91.6% overall accuracy across six risk tiers; compared with baseline models and single-source inputs reported in the same study, recall and warning lead time were more stable. Removing the riser channel and keeping only wellhead plus downhole reduced accuracy to approximately 88.1%, underscoring the contribution of cross-channel consistency to early detection and false-alarm reduction (Yin et al., 2021a).

Independent evidence also suggests that sequence classifiers can reduce false alarms without sacrificing recall when compared with single-signal thresholding, although performance remains data- and scenario-dependent (Obi et al., 2023).

Recommended reporting practice for tiered alarming includes: multi-level labels anchored in operating states and physical precursors; cross-channel time alignment and lag compensation to recover the "acoustic first, surface later" chronology; validation using chronologically ordered and leave-one-well-out protocols; and paired reporting of Δt and FNR, with FPR, AUC, and the confusion matrix as complements. The representative comparison is illustrated in Fig. 4.

3.3.2. Quantitative estimation: regression for downhole influx rate/volume

Beyond alarm generation, operational well control also requires quantitative estimation of influx magnitude. Yin et al. (2022) developed LSTM regression models to estimate instantaneous influx rate and cumulative influx volume after unified sampling and normalization of multi-source inputs, including rate of penetration, bottom-hole pressure, differential flow, surface equivalent circulating density, and riser acoustic amplitude. The five feature sets in Fig. 5 represent progressively richer monitoring configurations: drilling parameters only (Set 1), drilling parameters plus PWD (Set 2), drilling parameters plus surface ECD (Set 3), surface measurements plus PWD (Set 4), and surface measurements plus PWD plus riser acoustic amplitude (Set 5). Across four operating regimes—underbalanced, interbedded, complex interbedded, and highly fractured conditions—prediction error and response lag generally decrease as additional monitoring channels are incorporated, as illustrated in Fig. 5. The Set 4 model achieved a normalized RMSE of approximately 3.7%, whereas the Set 5 model further reduced the error to approximately 3% and maintained an inference latency of about 2–5 s, outperforming surface-only baselines in fast-evolving scenarios (Yin et al., 2022). Complementary simulator-based evidence also supports the feasibility of deep models for influx-size estimation under offshore drilling scenarios, while highlighting the need for careful field validation (Fjetland et al., 2019).

To ensure auditability, Yin et al. (2022) emphasize chronologically ordered splits, explicit event-onset rules and windowing, and standardized reporting of NRMSE, Δt, sample size, and computational load. Where necessary, prediction intervals or confidence bands can be reported to map regression outputs to operational safety limits.

In summary, quantitative estimation is most defensible when it (i) defines targets aligned with operating regimes, (ii) uses physics-anchored features such as flow-density coupling, bottom-hole-pressure rate of change, and riser acoustic energy, (iii) adopts time-ordered or leave-one-well-out validation with domain-wise reporting for transfer, and (iv) reports NRMSE, Δt, and inference latency as a minimal comparable set. Current evidence indicates that multi-source fusion can reduce errors and response lag under complex conditions (Yin et al., 2022; Fjetland et al., 2019).

4. Illustrative case study for intelligent gas kick detection

To improve the real-time accuracy and timeliness of early gas kick detection in ultra-deepwater drilling operations, Yin's team has developed an underwater gas kick early detection device based on the ultrasonic Doppler effect (Li et al., 2024). We call this device the underwater acoustic communication monitoring subsystem (UACMS). It assesses the gas kick conditions by identifying the gas content in the fluid in the riser annulus near the mudline. In addition, based on real-time multi-source monitoring of gas kick characteristics, we have also developed an integrated multi-source real-time monitoring system for early warning. Field trials in marine environments have shown that, under a water depth of 2023 m, this method can provide a warning at least 12 min earlier than traditional well logging.

4.1. Gas kick detection sonar integrated system

To illustrate how multi-source gas kick monitoring is implemented offshore, this section adopts the gas kick detection sonar integrated system as a concrete reference architecture. The gas kick detection sonar integrated system is designed to leverage the safety barriers of the underwater blowout preventer and the riser to enable non-contact gas kick detection in extreme deepwater conditions, reaching depths of 3000 m. As shown in Fig. 6, the system consists of two main components: the surface unit and the underwater unit, which handle data collection, transmission, and processing. The surface unit consists of a surface host and an acoustic module. The surface host, installed in the well logging monitoring room on the drilling platform, receives, processes, and displays data transmitted from the underwater system. The acoustic module is installed on the riser, 30–50 m below the surface, where it connects to the monitoring host and receives signals from underwater sensors. This design takes full advantage of the stable propagation and low attenuation of acoustic signals underwater, helping maintain reliable real-time data transmission.

The underwater unit comprises the gas kick monitoring module, the acoustic communication module, and ultrasonic, electromagnetic flow, pressure, and temperature sensors. Fig. 7 shows the structure and operating principle of the annular electromagnetic flow measurement device, which estimates annular flow velocity from the induced electromotive force based on Faraday's law of electromagnetic induction. The core sensing element is an ultrasonic Doppler sensor installed on the exterior of the riser, which detects changes in the movement of fluids inside the well. By analyzing Doppler frequency shifts in reflected acoustic waves, the system identifies flow changes associated with gas influx without inserting a sensor into the high-pressure flow path. This non-contact configuration reduces wear and failure risk relative to intrusive sensors and improves equipment durability in deepwater operations.

For data acquisition and transmission, the system employs an intelligent wake-up mechanism to save battery power. The acoustic communication module remains dormant and is awakened every 3 min to receive commands from the drilling platform. Upon detecting abnormal signals, the underwater monitoring unit transmits data every second, which is then uploaded to the surface unit for analysis. This adaptive working mode enables efficient, real-time data monitoring under low power consumption.

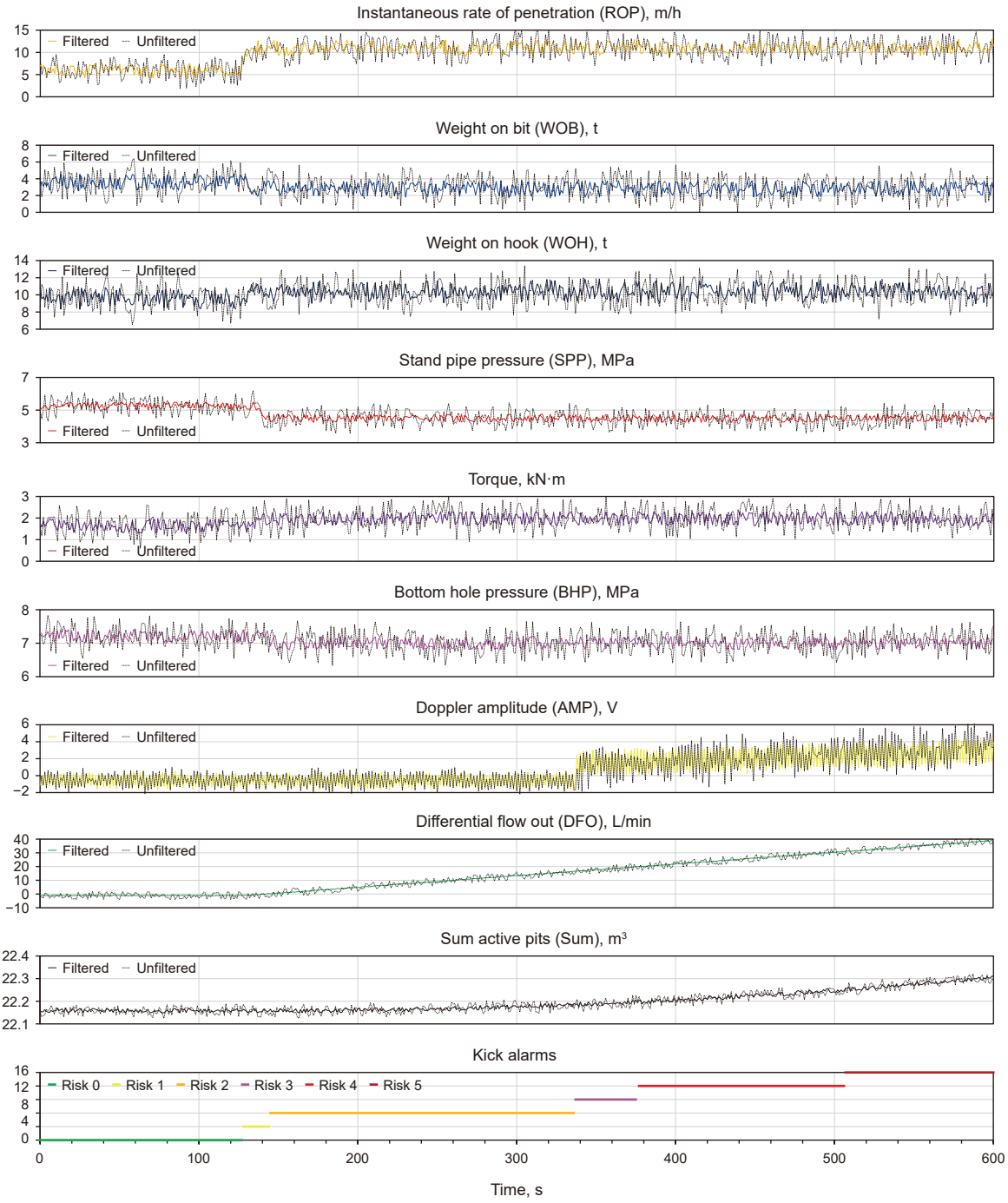


Fig. 4. Case study of gas kick-alarm classification (Yin et al., 2021a).

Furthermore, the device integrates multi-parameter fusion analysis, combining data from ultrasonic Doppler, pressure, and temperature sensors. In the upper-level system, related analysis software uses machine learning models to comprehensively process and analyze sensor data in real-time, identifying potential gas kick risks. This multi-parameter, multi-dimensional data fusion improves the system's detection accuracy and robustness, particularly in complex drilling environments.

The gas kick detection sonar integrated system uses the Doppler effect of ultrasonic signals to analyze fluid movement and transmits data to the surface monitoring system via an acoustic communication module. This design breaks through the limitations of traditional contact-based sensors, offering high sensitivity, low power consumption, and non-contact characteristics. It has shown excellent stability and reliability, particularly in high-pressure and corrosive deepwater environments. When integrated into an intelligent monitoring system, the device continuously tracks multiple parameters, including ultrasonic echoes, pressure, and temperature, allowing it to detect subtle changes in the gas–liquid mixture within the wellbore. This capability provides reliable and efficient data support for the intelligent early warning system.

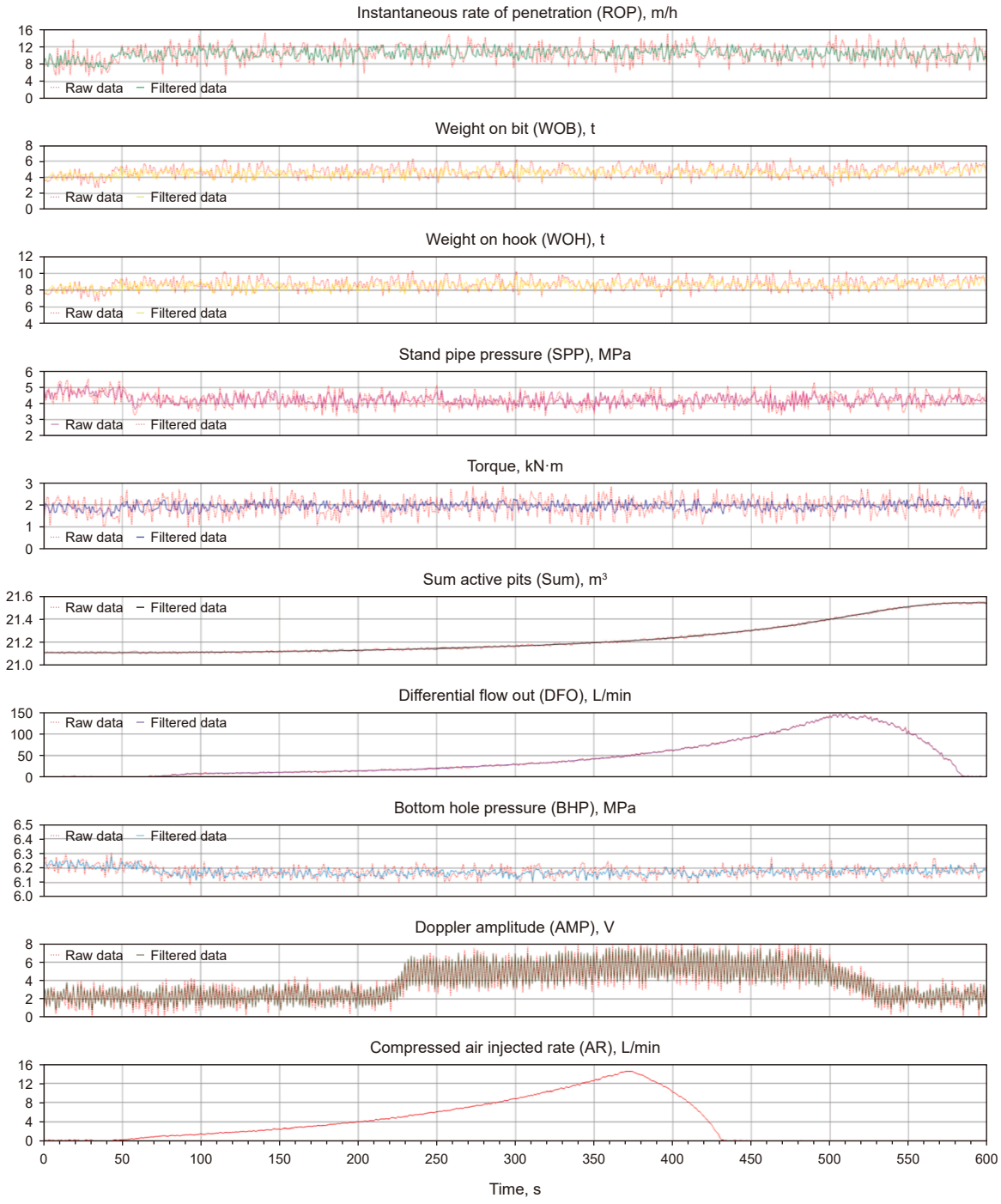


Fig. 5. Case study of gas-kick-alarm quantitative detection (Yin et al., 2022).

4.2. Optimization strategies for monitoring systems

Using the newly developed gas kick detection sonar integrated system as the core hardware, Yin's research team designed a data interaction scheme between the surface, riser, and downhole systems for real-time monitoring and information transmission in deepwater drilling environments. This system integrates measurement while drilling (MWD), the underwater ultrasonic Doppler monitoring device, and the acoustic communication module, enabling data sharing and real-time transmission between the downhole, riser, and surface platforms through the wellsite information transfer standard markup language (WITSML) protocol. Compared to traditional single-channel data communication methods, this design significantly enhances the efficiency and reliability of data transmission, ensuring the rapid acquisition of accurate information even in complex deepwater operational environments, thus safeguarding early risk detection.

4.2.1. Pilot-well testing

This pilot test was designed to produce synchronized, high-rate multichannel time series for model training and validation. To obtain multi-source, high-sampling-rate data under reproducible

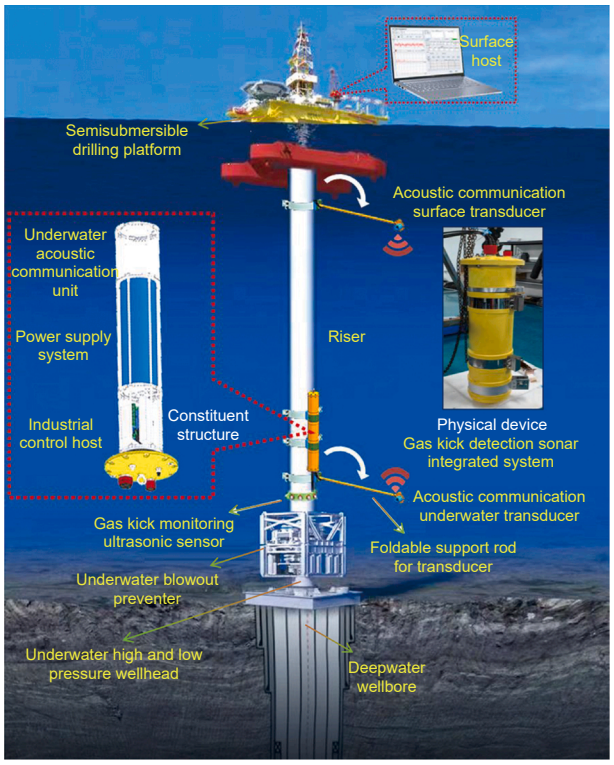


Fig. 6. Schematic diagram of kick detection and warning system for ultra-deepwater drilling (Li et al., 2024).

conditions, a pilot-well gas-influx simulation was conducted, generating a vertically comprehensive dataset spanning surface, riser, and downhole channels. The experimental system comprised the wellbore, rig and bottom-hole assembly (BHA), a gas-injection unit, and a data acquisition and processing system, supplemented by SK-ALS mud logging and a portable module for field-grade real-time acquisition and visualization. Monitored variables included surface operational parameters and differential flow-out (DFO) measured with Coriolis and gate flowmeters in parallel, mud-pit volumes (Pit1, Pit2, Sum), riser Doppler acoustic amplitude (AMP), and bottom-hole pressure (BHP), with gas-injection rate and choke pressure recorded jointly to characterize influx magnitude and dynamics. Compressed air was injected programmatically under different conditions—activated while drilling sandstone intervals and halted in shale—to emulate field kicks upon encountering overpressured sand bodies. Key parameters (mud density and viscosity, influx size, inflow rate) were systematically swept to generate training and validation sequences.

To ensure consistency with target offshore conditions, geometric-similarity scaling was applied. Casing diameter and well depth were scaled by factors of 1.7 and 10, respectively; static pressure and gas–liquid interactions were calibrated to preserve high-pressure/high-temperature solubility and kinetics; and other critical parameters were adjusted by a factor of 22.5 so that pilot dynamics approximate those of Well X-1-3 in the South China Sea. The resulting multi-source time-series dataset contains 62,028,000 records, uniformly normalized and split in chronological order into training, validation, and test sets. Hyperparameters were batch size 128, 50 epochs, Adam optimization, and L2 regularization ($\alpha = 1 \times 10^{-4}$), with grid search and convergence checks performed without shuffling sequences. On this pilot dataset, a two-layer Bi-LSTM (60 units per layer, dropout 0.2) exhibited stable performance across hidden-layer and node configurations and achieved a maximum R^2 of 92.36%, providing quantitative support for model selection and threshold calibration prior to sea trials (Yin et al., 2025).

4.2.2. Multi-source information fusion

Fig. 8 presents the multi-source information-fusion detection and early-warning workflow reported by the authors. The workflow uses a hybrid modeling architecture to improve recognition of early gas kick signatures. A Y-pipe hydrodynamic model was introduced and coupled with Kalman filtering to fuse and interpret multi-sensor observations. Within this framework, key variables such as drilling pump pressure and inferred downhole flow behavior are monitored in real time, and abnormal patterns are mapped to an early-warning output for operational decision support.

Fig. 9 provides the hydraulic schematic for the double Y-pipe spill monitoring method. The method involves two coupled circulation models: the large-Y circulation describes the interaction

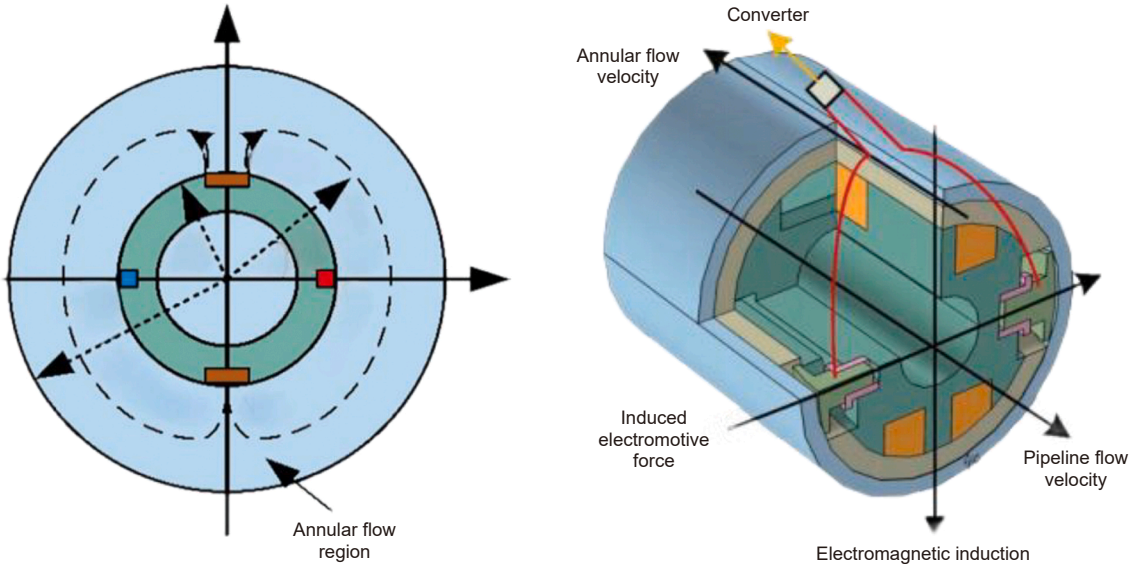


Fig. 7. Structure and operating principle of the annular electromagnetic flow measurement device.

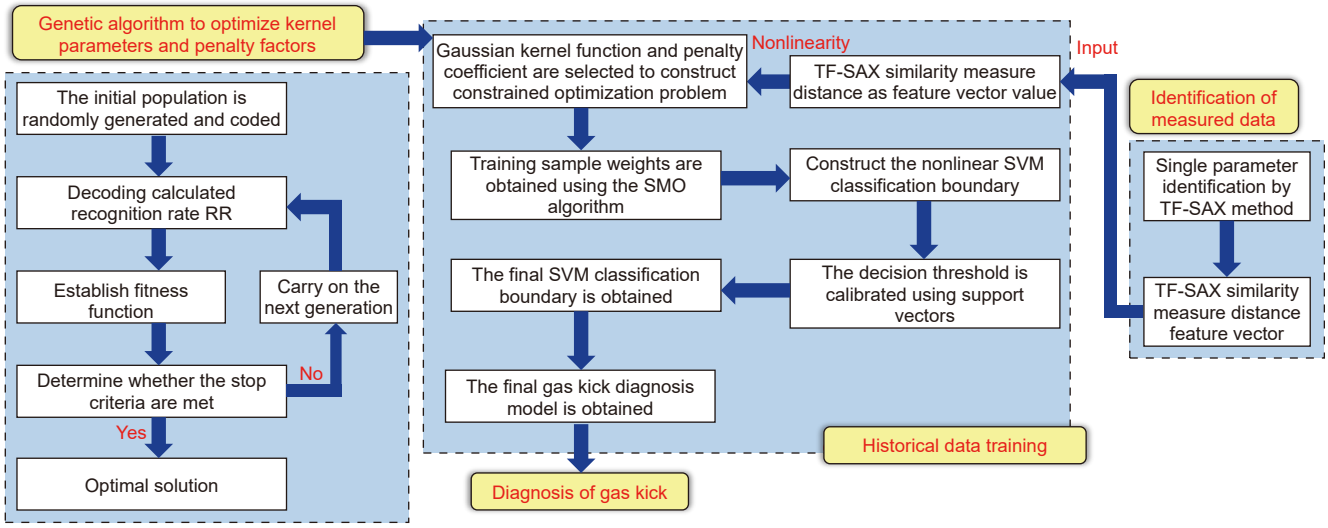


Fig. 8. Schematic diagram of multi-parameter collaborative gas kick risk warning method.

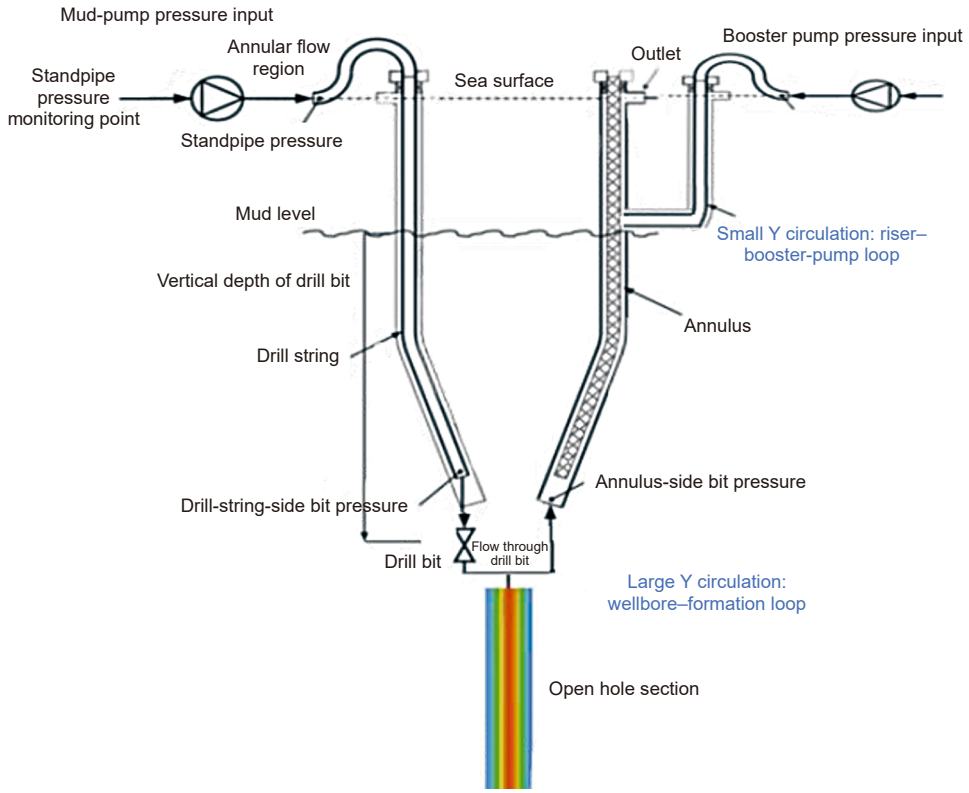


Fig. 9. Schematic diagram of deepwater double Y-pipe spill monitoring method (Stamnes et al., 2008).

between bottom-hole formation-fluid influx and mud-system dynamics, whereas the small-Y circulation monitors pressure fluctuations between the riser annulus and the booster-pump loop. By merging these two data sources into a unified predictive framework, the system can assess early gas kick characteristics with support from Kalman filtering and can provide a more physically constrained warning than a single-pipe model.

Compared with a traditional single-pipe approach, the double Y-pipe structure is intended to increase sensitivity to gas–liquid two-phase interactions and to strengthen early-warning precursors. To capture Doppler acoustic signals from the riser segment, the authors optimized the sensing layout and applied deep-learning decoding to separate gas kick signatures from interference noise. In the reported experiments, a Bi-LSTM-based classifier showed stable performance under noisy conditions, supporting the feasibility of the proposed decoding-and-fusion strategy.

Another key innovation of the double Y-pipe method is integrating Kalman filtering with deep learning models, enabling dynamic fusion and real-time analysis of multi-source data. Kalman filtering predicts and corrects model parameters, ensuring data consistency and accuracy. Meanwhile, deep learning models

extract high-level features from the fused data, allowing for detailed classification and early warning of gas kick risks.

4.3. Model development and testing

4.3.1. Drilling data processing

To support early and reliable detection of gas kicks in deepwater environments, the research team performed comprehensive processing of multi-source drilling data. The analysis began with the identification of parameters sensitive to gas influx, including annular pressure, mud-pit volume, outlet flow rate, and rate of penetration. Fig. 10 compares raw measurements with filtered signals and demonstrates why sliding-window adaptive filtering is required before model training. The filtering step reduces high-frequency noise while preserving low-amplitude trend changes that may represent early gas-influx precursors under offshore operating conditions.

In addition, a nonlinear state-space model of the wellbore-formation system was constructed using an extended Kalman filter (EKF). This model accounted for time-varying noise, sensor drift, and dynamic coupling among pressure, flow, and formation resistance. Through Taylor-series linearization and covariance matrix adjustment, the process noise was effectively separated from measurement noise, improving the precision of parameter estimation in high-noise environments. These preprocessed features were further used to calibrate key physical parameters, such as APWD fluctuations and resistivity changes associated with gas intrusion.

4.3.2. Core method of multi-source information fusion detection algorithm

A hybrid diagnostic framework was developed that integrates symbolic feature encoding and supervised learning. Time-series data from multiple sensors were transformed using trend feature symbolic aggregate approximation (TF-SAX), a method that enables symbolic representation of fluctuations in downhole parameters such as drilling pump pressure, resistivity, and ultrasonic intensity. This transformation captured temporal patterns linked to the onset of gas influx.

These symbolic features were used as inputs to a SVM-based classification model. The SVM model mapped multi-dimensional inputs into a high-dimensional feature space and defined an optimal decision boundary to distinguish between normal and gas kick conditions. The model adaptively adjusted parameter weights based on operating context and new sample inputs, enhancing its stability and generalization. Compared to traditional single-threshold detection, this approach significantly improved diagnostic accuracy while reducing false positives.

4.3.3. Field validation and performance evaluation

A sea trial was conducted on an ultra-deepwater exploration well in the South China Sea at a water depth of approximately 2000 m. As summarized in Fig. 11, the sea-trial workflow included deck-side preparation, deployment of the underwater monitoring device, acoustic communication testing, riser-mounted operation, recovery, and post-test data analysis. The monitoring system comprised a topside unit and a subsea master unit installed on the riser near the mudline. After a power-on self-test, the system operated in nominal transmission mode at fixed intervals and switched automatically to alarm mode upon detecting an evolving anomaly. To ensure data integrity, the subsea unit also recorded data to local storage (about 7.61 MB in total), later retrieved at a deck-side port. Communication remained stable throughout, with no link interruptions affecting decision logic.

Acquisition was archived by calendar day and operational phase. Two 6-h windows were analyzed in detail: 18:00–24:00 on January 28 and 00:00–06:00 on January 29. Conventional mud-logging channels (flow-out, pit volume, gas readings) were recorded on the logging side. The monitoring side captured Doppler ultrasonic amplitude near the riser mudline and derived features; temperature and pressure traces were used for operating-state screening and removal of non-stationary intervals. Across the trial, ultrasonic, temperature, and pressure were collected in real time and stored offline (ultrasonic: 939,402 samples; temperature/pressure: 939,346 samples). Ambient temperature was stable at about 3.2 °C (±0.1 °C), and the pressure trace was stable within instrument precision (±0.2 MPa). This field validation evaluated early-warning lead time (Δt) only; regression errors and classification accuracy were not assessed.

Δt was defined as follows. Let t_{US} be the time when the ultrasonic channel first reaches and then continuously exceeds a threshold for τ s, and let t_{LOG} be the time when the logging baseline (pit volume or differential flow) first exhibits and then continuously maintains a significant deviation for τ s; then $\Delta t = t_{LOG} - t_{US}$.

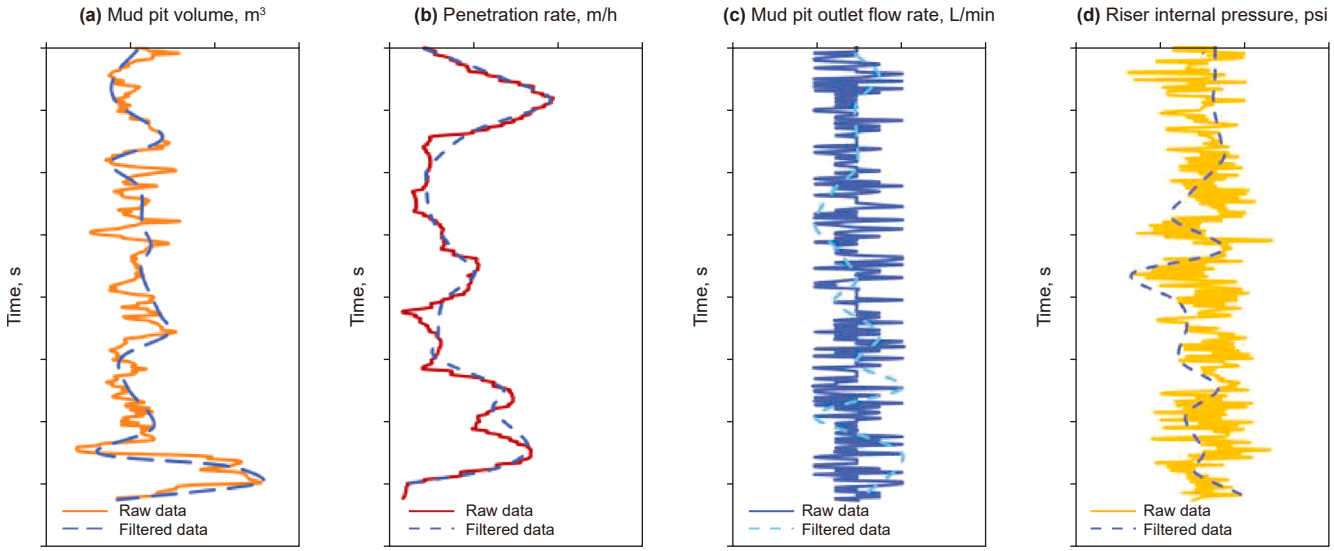


Fig. 10. Comparison of raw data with filtered data.

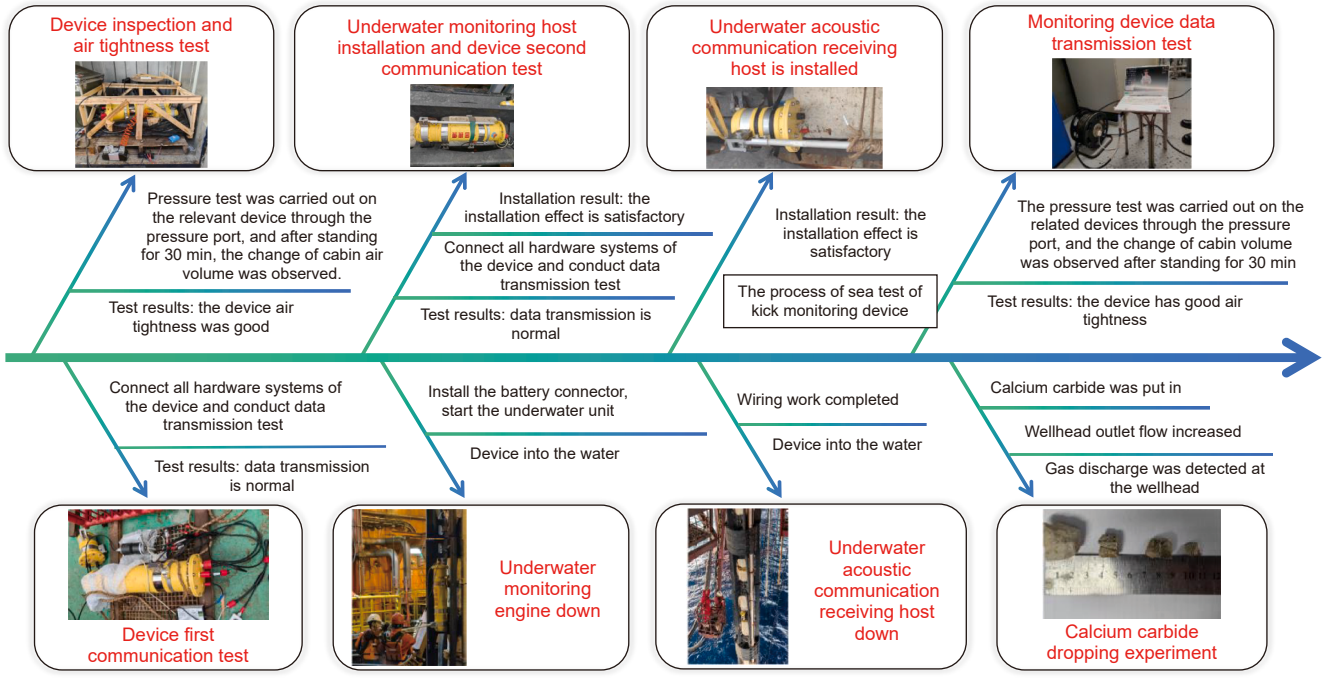


Fig. 11. Sea-trial workflow of the kick-monitoring system.

Criteria and thresholds were fixed prior to the trial and remained unchanged. For robustness, a ±10% threshold-sensitivity check was performed without altering the decision structure, and online records were cross-validated against offline storage.

Field results for the two analysis windows. Ultrasonic energy exceeded the adaptive threshold prior to logging anomalies (pit-volume rise or flow-out deviation), demonstrating an "ultrasound first, logging later" sequence consistent with the Δt definition.

Relative to logging baselines, the device delivered stable early-warning performance. Under multiple intentional gas-injection conditions, the minimum reproducible lead time was ≥12 min, and several intervals showed 25–35 min advances. No false triggers occurred during non-injection disturbance periods, indicating that annular-flow compensation and the two-stage logic effectively filtered pump transients and short-term circulation fluctuations. Sensitivity tests showed that ±10% threshold perturbations preserved both the magnitude and relative ordering of Δt; lead times remained >10 min, within an operationally meaningful early-warning range.

This sea trial was a read-only comparison across multiple segments of a single well, implying higher statistical uncertainty than the pilot setting. FPR, FNR, AUC, and other classification metrics were not quantified. Basin-wide deployment will require recalibration and chronologically ordered evaluation across multiple wells and operating conditions to quantify the effects of geological and operational variability on thresholds and compensation coefficients.

5. Deployment considerations for deepwater gas kick monitoring

5.1. High-precision, diversified sensors

Reliable early gas kick recognition in deepwater drilling depends on high-quality data acquisition. To reduce measurement interference and capture weak early kick signatures, Yin's research team developed two riser bypass nipples with different sensing mechanisms, as described below.

5.1.1. Gas influx riser Doppler sensor bypass nipple

The research team designed and developed a new bypass nipple for the riser, incorporating an ultrasonic Doppler sensor on the bypass pipe to monitor the gas kick migration pattern. As shown in Fig. 12, the short side-bypass pipe creates an independent flow path for drilling fluid and positions the acoustic transmitter and receivers away from the rotating drill pipe. A configuration with one transmitter and six receivers at the same elevation and spaced 60° apart was adopted. Based on the data-acquisition frequency and drilling-fluid flow rate, the receivers were placed downstream of the transmitter to capture displaced acoustic signals from the drilling fluid. This design resolves the signal distortion problem typically encountered with Doppler sensors outside the riser.

5.1.2. Riser mass weighing bypass nipple

Fig. 13 illustrates the riser mass weighing bypass nipple proposed for gas-influx monitoring. This design establishes a liquid circulation loop between the riser and the containment device, utilizing a weight detection device to monitor changes in liquid weight in real-time, enabling precise gas kick monitoring. In this system, the liquid flows from the riser to a sealed chamber in the containment device via the first interface. Then, it returns to the riser through the second interface, forming a continuous liquid loop. By capturing minute changes in liquid weight, the weight detection device accurately detects gas influx and determines the gas content in the incoming fluid. The novelty of this approach lies in the combination of liquid circulation and weight detection, which overcomes the limitations of traditional ultrasonic Doppler monitoring systems that are affected by drill pipe disturbances, enabling real-time and precise gas kick monitoring. Additionally, this monitoring method is user-friendly and easy to implement, offering a high-efficiency and reliable gas kick detection solution

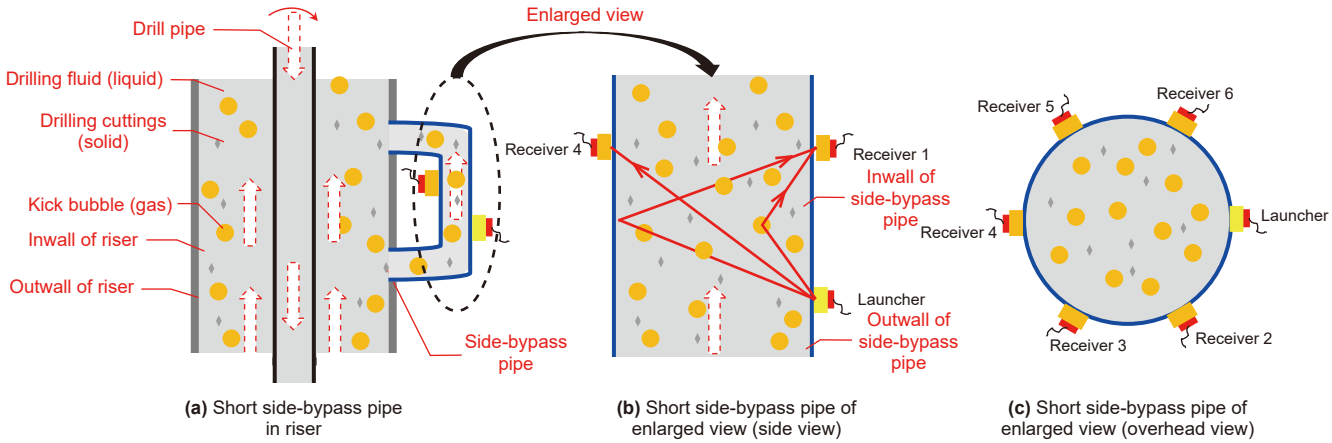


Fig. 12. Short side-bypass pipe in the marine riser and Doppler sensor layout: **(a)** overview; **(b)** enlarged side view; **(c)** enlarged plan view (Yin et al., 2023).

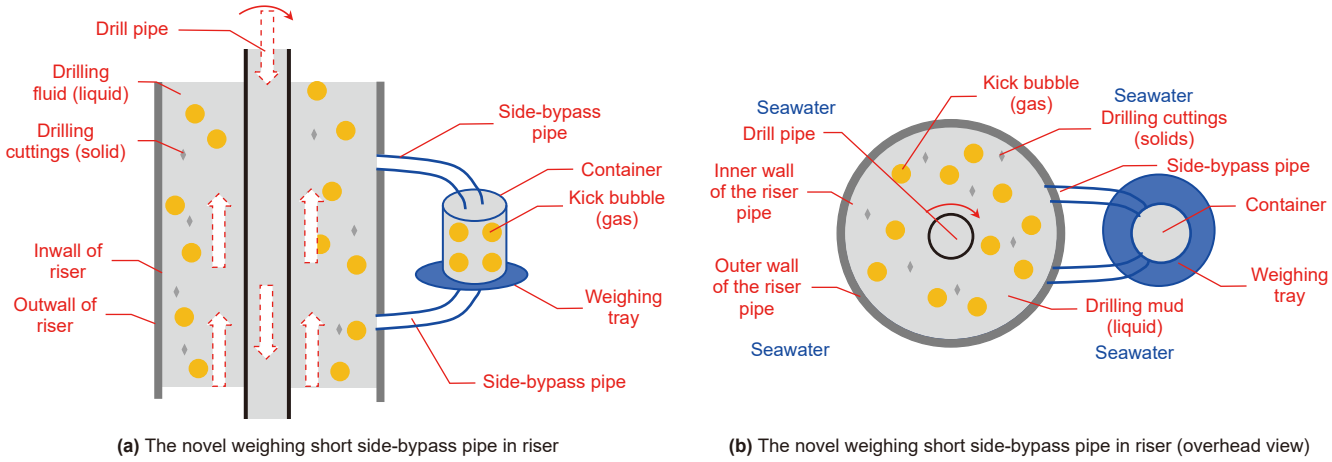


Fig. 13. Schematic of the riser mass weighing bypass nipple: **(a)** assembly overview; **(b)** plan view.

that significantly enhances the safety and efficiency of deepwater drilling operations.

5.2. Geological and operational diversity: impacts on robustness and retraining

The case evidence in this paper is primarily from deepwater South China Sea wells, characterized by interbedded sand and shale with relatively concentrated pressure regimes and consistent operational rhythms. To avoid extrapolation bias from a single basin, this section compares—under a unified protocol—the lithology, pressure regime, rig and riser layout, and sensor suite of three representative deepwater settings: the South China Sea, the Gulf of Mexico, and the Campos Basin, and links these factors to signal observability, domain-drift risk, and recommended retraining frequency. In summary, lithologic differences alter influx phase behavior and the relative sensitivity of sensing channels; the pressure regime and the width of the safe mud-weight window govern the trade-off between Δt and FNR/FPR; water depth and riser length affect surface-channel latency through mud compressibility and waveform dispersion; and rig layout together with sensor configuration sets the ceiling for multi-source fusion and the difficulty of time alignment.

At the model level, most statistical or deep models are more stable across multiple wells within the same block, whereas cross-basin transfer degrades performance due to covariate drift (operations, mud systems, acoustic propagation) and concept drift (differences in alarm logic and operational thresholds). Robust assessment should therefore use chronologically ordered splits or leave one well out domain-wise validation, with small-sample recalibration early in transfer. Where equipment and organizational conditions permit, domain adaptation or transfer learning and online threshold recalibration can materially reduce extrapolation loss; otherwise, lightweight retraining combined with drift monitoring (distribution drift, threshold drift, and alarm-rate drift) provides the minimum safeguard.

5.3. More refined data preprocessing methods

As a case study, we present the effective feature extraction of ultrasonic Doppler signals from the riser as part of the data preprocessing process. The ultrasonic Doppler signals from the bypass nipple of the gas influx riser are influenced by several factors, including gas influx rate, drilling fluid discharge, drilling fluid density, and the properties of the drilling fluid. The response of the acoustic signal is complex, and effectively extracting meaningful features is challenging. Identifying the acoustic propagation path and data denoising are critical, along with studying the time-domain characteristics of the acoustic signal and the influence of various factors on it. This research used time-frequency and linear

transformations to extract effective features from ultrasonic Doppler signals. These are key prerequisites for understanding the evolution mechanisms of gas kicks and enabling early warning systems.

The authors analyzed time-domain characteristics of Doppler signals against operational factors such as gas-injection rate, drilling-fluid discharge, fluid density, and rheology. After denoising (e.g., Fourier- and wavelet-based filtering), they applied time-frequency transforms (e.g., fast Fourier transform and short-time Fourier transform) and linear feature transforms (e.g., PCA, independent component analysis (ICA), and linear discriminant analysis (LDA)) to extract representative descriptors, including amplitude peaks, wave speed, dominant frequency, and attenuation coefficients. Correlation analysis across surface, riser, and downhole parameters was then used to screen candidate inputs for subsequent modeling and fusion.

5.4. Development of an intelligent gas kick early warning system

To integrate the previously discussed research findings and achieve early intelligent recognition of gas kicks in deepwater drilling, Yin's research team developed an intelligent gas kick early warning system. This system is designed around real-time data collection, transmission, storage, and model analysis to provide efficient and reliable technical support for deepwater well control safety.

5.4.1. System workflow

The workflow of the intelligent gas kick early warning system for deepwater drilling, as illustrated in Fig. 14, consists of six key technical components: (1) data collection through sensors and integrated well logging instruments; (2) data transmission based on the WITSML protocol; (3) time series data storage (e.g., cloud computing); (4) high-performance computing platforms (e.g., workstations used to build data-driven models); (5) the deepwater drilling gas kick early intelligent recognition system; (6) real-time analysis of time-series drilling data to identify gas kick risks, perform downhole gas kick quantification, issue early warnings, and develop deepwater well control strategies. This system ensures safe deepwater operations, reduces costs, and improves efficiency.

5.4.2. System architecture design

The proposed intelligent gas kick early warning system adopts a modular architecture to support robust, scalable, and field-deployable detection capabilities under deepwater drilling conditions. It comprises five core functional modules that integrate seamlessly with existing drilling infrastructure while enabling real-time risk identification, decision support, and operational guidance.

Data communication module: This module establishes high-throughput, low-latency connectivity between downhole and surface-level equipment, including integrated logging instruments, early kick detection (EKD) sensors, and PWD tools. The Transmission Control Protocol/Internet Protocol (TCP/IP) suite ensures stable data acquisition across distributed components, enabling synchronized monitoring under dynamic drilling conditions.

Data storage module: Acquired data are encoded in WITSML format and transmitted to a structured query language (SQL) based database to support real-time storage and retrospective analysis. The system facilitates structured and unstructured data visualization through user interfaces tailored to field engineers and remote operators. Historical datasets remain traceable and readily available for model optimization, anomaly backtracking, and decision validation.

Gas kick recognition module: As the analytical core of the system, this module integrates time-series learning algorithms based on LSTM networks to classify kick severity levels, estimate downhole gas influx rates, and issue predictive alarms. The module supports automated cross-platform communication to alert control centers and expert systems, enabling rapid risk response across offshore platforms and centralized supervision facilities.

Well control strategy module: Upon detection of abnormal conditions, this module synthesizes real-time data and predictive outputs to recommend control actions. These include managed pressure drilling (MPD) adjustments for low-to-moderate risks and automated generation of detailed well control plans under high-risk scenarios. Recommendations cover optimized mud weight, pump stroke calculations, shut-in procedures, and contingency workflows aligned with standard well control protocols.

Auxiliary function module: To ensure practical usability and field adaptability, the system incorporates supplementary features

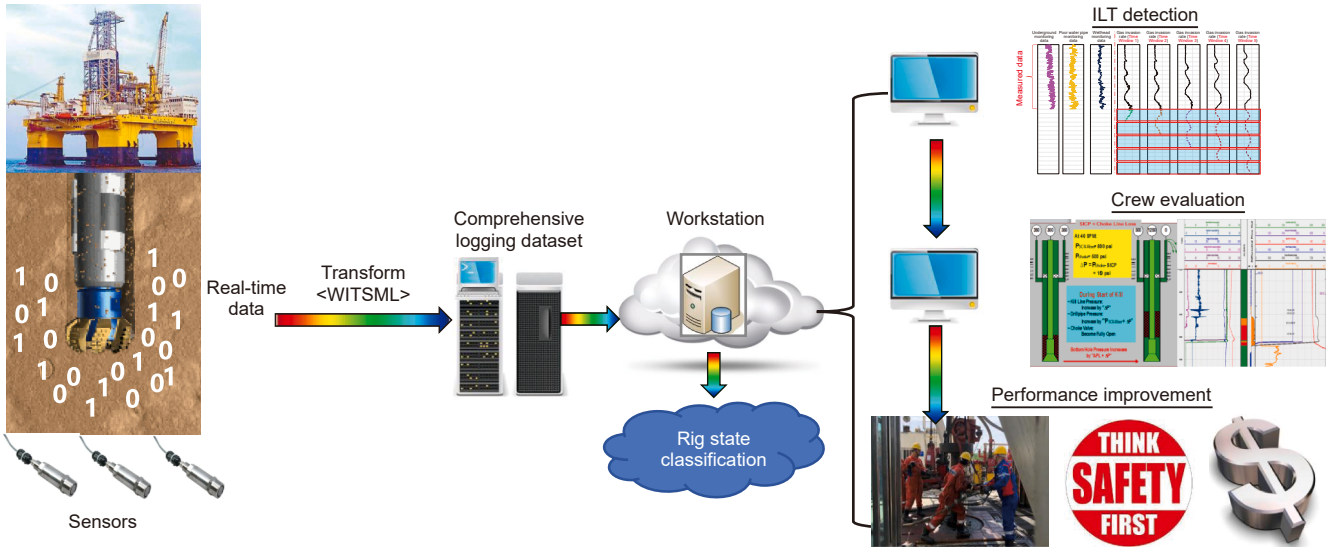


Fig. 14. Proposed workflow for data-driven modeling to improve drilling performance in offshore batch wells (Yin et al., 2020b).

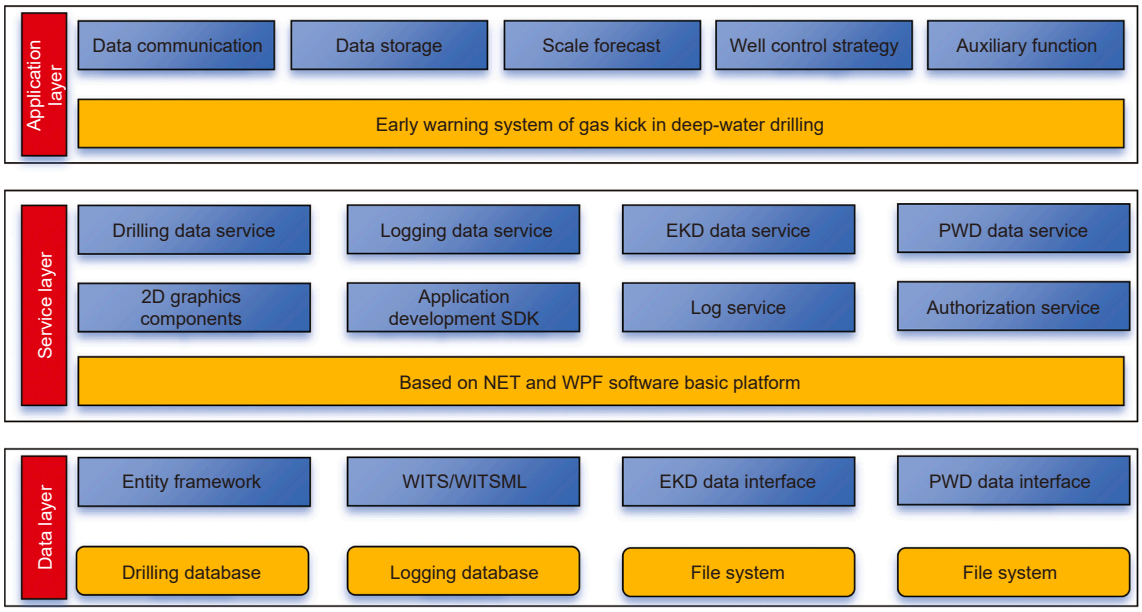


Fig. 15. Development content of early warning system for gas kick in deepwater drilling (Yin et al., 2023).

such as historical data playback for post-event diagnostics, engineering unit converters, embedded operation manuals, and secure shutdown functions. These components are designed to streamline deployment, reduce human error, and facilitate continuous use under high-stress operational conditions.

Overall, the system architecture emphasizes practical deployment, cross-domain integration, and decision autonomy. Its layered modularity enhances adaptability to various wellsite configurations, enabling intelligent kick detection and response workflows suited for real-time operation in high-risk deepwater drilling environments.

5.4.3. System implementation details

The development of the intelligent gas kick early warning system for deepwater drilling comprises three layers, as shown in Fig. 15: the application layer, the service layer, and the data layer.

The application layer performs gas kick risk classification, downhole gas kick quantification, downhole pressure control, and well control design using filtered time-series data.

The service layer visualizes real-time data and prediction results based on WITSML standards and the TCP/IP protocol.

The data layer uses Microsoft SQL Server 2008 as the database management system and applies object-oriented development techniques to facilitate data querying and result storage. This layer primarily manages real-time drilling data, well logging data, gas kick risk predictions, well control records, pre-input expert knowledge, and system login information. It provides functions for data retrieval, modification, addition, and deletion.

The development and application of this system demonstrate that through deep analysis of multi-source drilling data and comprehensive use of intelligent algorithms, early identification and risk classification of gas kicks in deepwater drilling can be effectively achieved. The system outputs feed directly into MPD pressure adjustments. Future improvements will enhance the model's accuracy and real-time performance while refining the expert database and remote consultation functionality to support more efficient, cost-effective, and safe deepwater drilling operations.

6. Conclusions and perspectives

6.1. Conclusions

This study presents a comprehensive review and methodological advancement in gas kick detection technologies for deepwater drilling, addressing the critical safety challenges posed by complex downhole environments and delayed surface responses. By systematically analyzing the evolution of experimental methods, sensor integration, and machine learning applications, this work highlights the transition from reactive monitoring to intelligent early warning systems.

(1) Experimental simulations and field-based monitoring serve as foundational tools in understanding gas influx dynamics. Techniques such as ultrasonic and Doppler-based sensing, coupled with riser pressure diagnostics, enhance early detection capabilities under high-pressure, high-temperature (HPHT) conditions typical of ultra-deepwater environments.

(2) Machine learning, particularly LSTM and deep neural networks, enables the recognition of weak, nonlinear patterns in high-noise time-series data, outperforming traditional physical models in early-stage detection. These algorithms empower systems to provide real-time classification, quantification, and risk-level differentiation of gas influx events.

(3) Advanced feature engineering, including the use of dimensionality reduction techniques such as PCA and mutual information, improves the efficiency and accuracy of ML models by ensuring optimal input selection. Temporal-spatial features captured from downhole and surface sensors form the basis of intelligent recognition modules.

(4) Integration of AI with physical modeling and distributed sensing has shown promise in reducing false alarms and improving robustness. However, scalability across different geologies and real-time deployment across operational platforms remain open challenges.

The proposed multi-source data fusion approach, combining surface, riser, and downhole information with deep learning architectures, demonstrates superior performance in early kick detection. The system reduces false positives and enhances predictive timeliness, thereby supporting safer and more efficient well control decision-making.

6.2. Future perspectives

Deepwater kick monitoring is shifting from early detection to explainable, scalable, and actionable systems. The path forward should focus on four concise priorities.

(1) Tie model evidence to drilling physics—BHP trend, ECD change, differential flow-density coupling, and riser acoustic energy—so alarms are auditable and acceptable on rig.
(2) Make monitoring easy to deploy. Keep one robust anchor channel in surface, riser, and downhole, unify sampling and timestamps, and automate calibration, drift checks, and event tagging at the edge.
(3) Link early detection to governed control. Move from read-only to advisory to constrained linkage with MPD and BOP, and attach clear adjustment guidance and an audit trail to each alert.
(4) Standardize time alignment across channels and report a compact risk set—probability of influx, likely rate, and time to escalation—to improve well control hand-offs and retraining decisions.

CRediT authorship contribution statement

Qi-Shuai Yin: Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **Zhi-Ming Yin:** Writing – review & editing, Validation, Project administration, Investigation, Funding acquisition. **Zheng-Qiang Xu:** Writing – review & editing, Writing – original draft, Visualization, Software, Investigation, Formal analysis, Data curation. **Meng-Bo Li:** Visualization, Supervision, Resources, Project administration. **Lai-Bin Zhang:** Writing – review & editing, Supervision, Resources, Conceptualization. **Jin Yang:** Writing – review & editing, Supervision, Resources, Funding acquisition, Conceptualization. **Dan Sui:** Writing – review & editing, Validation, Project administration, Investigation, Formal analysis. **Ying-Ying Guo:** Writing – review & editing, Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This paper is financially supported by the National Natural Science Foundation of China (NSFC: Nos. U22B20126 and 52374020), the National Key Research and Development Program (No. 2022YFC2806500), and scientific and technological projects entrusted by enterprises and public institutions (No. CCL2022RCPS2008XNN), Beijing Nova Program (No. 20250484913) and Science Foundation of China University of Petroleum, Beijing (No. 2462025QNXZ009).

References

Aljubran, M., Ramasamy, J., Albassam, M., et al., 2021. Deep learning and time-series analysis for the early detection of lost circulation incidents during drilling operations. IEEE Access 9, 76833–76846. https://doi.org/10.1109/ACCESS.2021.3082557.

Borozdin, S., Dmitrievsky, A., Eremin, N., et al., 2020. Drilling problems forecast system based on neural network. In: SPE Annual Caspian Technical Conference. SPE 202546–MS. https://doi.org/10.2118/202546-MS.

de Oliveira Werneck, R., Prates, R., Moura, R., et al., 2022. Data-driven deep-learning forecasting for oil production and pressure. J. Petrol. Sci. Eng. 210, 109937. https://doi.org/10.1016/j.petrol.2021.109937.

Fan, X., Shuai, J., Li, Z., et al., 2020. Research status and prospect of oil and gas well early overflow monitoring technology. Drill. Prod. Technol. 43 (3), 23. https://doi.org/10.3969/J.ISSN.1006-768X.2020.03.08 (in Chinese).

Feng, K., Liu, S., Yin, Z., et al., 2025. Gas kick and lost circulation risk identification method with multi-parameters based on support vector machine for drilling in deep or ultradeep waters. Eng. Sci. Technol. Int. J. 64, 102007. https://doi.org/10.1016/j.jestch.2025.102007.

Fjetland, A.K., Zhou, J., Abeyrathna, D., et al., 2019. Kick detection and influx size estimation during offshore drilling operations using deep learning. In: 2019 14th IEEE Conference on Industrial Electronics and Applications (ICIEA). IEEE, pp. 2321–2326. https://doi.org/10.1109/ICIEA.2019.8833850.

Fraser, D., Lindley, R., Moore, D., et al., 2014. Early kick detection methods and technologies. In: SPE Annual Technical Conference and Exhibition. SPE 170756–MS. https://doi.org/10.2118/170756-MS.

Gu, Q., Fallah, A., Ashok, P., et al., 2021. Real-time multi-event anomaly detection using elliptic envelope and deep neural network for enhanced MPD robustness. In: SPE/IADC Managed Pressure Drilling Conference. SPE-206399-MS. https://doi.org/10.2118/206399-MS.

Hargreaves, D., Jardine, S., Jeffryes, B., 2001. Early kick detection for deepwater drilling: New probabilistic methods applied in the field. In: SPE Annual Technical Conference and Exhibition. SPE 71369–MS. https://doi.org/10.2118/71369-MS.

Ifenaike, A.O., Oluwadare, O.B., 2024. Advancing drilling safety: Automated anomaly detection in well control using machine learning techniques. In: SPE Nigeria Annual International Conference and Exhibition. SPE 221626–MS. https://doi.org/10.2118/221626-MS.

Jiang, Q., Gao, D., Zhong, L., et al., 2020. Quantitative sensitivity and reliability analysis of sensor networks for well kick detection based on dynamic Bayesian networks and Markov chain. J. Loss Prev. Process. Ind. 66, 104180. https://doi.org/10.1016/j.jlp.2020.104180.

Johnson, A., Leuchtenberg, C., Petrie, S., et al., 2014. Advancing deepwater kick detection. In: IADC/SPE Drilling Conference and Exhibition. SPE 167990–MS. https://doi.org/10.2118/167990-MS.

Keil, A., Bernat, E.M., Cohen, M.X., et al., 2022. Recommendations and publication guidelines for studies using frequency domain and time-frequency domain analyses of neural time series. Psychophysiology 59 (5), e14052. https://doi.org/10.1111/psyp.14052.

Krishna, S., Ridha, S., Vasant, P., et al., 2020. Conventional and intelligent models for detection and prediction of fluid loss events during drilling operations: A comprehensive review. J. Petrol. Sci. Eng. 195, 107818. https://doi.org/10.1016/j.petrol.2020.107818.

Li, C., Zhu, Z., Cui, Y., et al., 2025. Intelligent kick warning model based on machine learning. Processes 13 (7), 2162. https://doi.org/10.3390/pr13072162.

Li, G., Song, X., Tian, S., et al., 2022a. Intelligent drilling and completion: A review. Engineering 18, 33–48. https://doi.org/10.1016/j.eng.2022.07.014.

Li, X., Zhang, J., Tang, X., et al., 2022b. Propagation characteristics and application effects of measurement-while-drilling pressure wave for early gas-kick detection. J. Loss Prev. Process. Ind. 76, 104741. https://doi.org/10.1016/j.jlp.2022.104741.

Li, Z., Yin, Z., Tian, D., 2024. Research progress on well control risk management technology for deep sea and ultra-deep water drilling. Drill. Prod. Technol. 47 (4), 8–17. https://doi.org/10.3969/J.ISSN.1006-768X.2024.04.02 (in Chinese).

Maus, L.D., Tannich, J.D., Ilfrey, W.T., 1979. Instrumentation requirements for kick detection in deep water. J. Petrol. Technol. 31 (8), 1029–1034. https://doi.org/10.2118/7238-PA.

Meng, Y., Xu, C., Wei, N., et al., 2015. Numerical simulation and experiment of the annular pressure variation caused by gas kick/injection in wells. J. Nat. Gas Sci. Eng. 22, 646–655. https://doi.org/10.1016/j.jngse.2015.01.013.

Mills, I., Reitsma, D., Hardt, J., et al., 2012. Simulator and the first field test results of an automated early kick detection system that uses standpipe pressure and annular discharge pressure. In: SPE/IADC Managed Pressure Drilling and Underbalanced Operations Conference and Exhibition. SPE-156902-MS. https://doi.org/10.2118/156902-MS.

Molaei, A., Nikoofard, A., Sedigh, A.K., et al., 2023. Parameter and state estimation of managed pressure drilling system using the optimization-based supervisory framework. IEEE Trans. Control Syst. Technol. 31 (6), 2937–2944. https://doi.org/10.1109/TCST.2023.3273192.

Muojeke, S., Venkatesan, R., Khan, F., 2020. Supervised data-driven approach to early kick detection during drilling operation. J. Petrol. Sci. Eng. 192, 107324. https://doi.org/10.1016/j.petrol.2020.107324.

Nybø, R., Bjørkevoll, K.S., Rommetveit, R., 2008. Spotting a false alarm—integrating experience and real-time analysis with artificial intelligence. In: Intelligent Energy Conference and Exhibition SPE 112212–MS. https://doi.org/10.2118/112212-MS.

Obi, C.E., Falola, Y., Manikonda, K., et al., 2022. A machine learning analysis to relate flow pattern and pressure gradient during gas kicks. In: SPE Western Regional Meeting. https://doi.org/10.2118/209333-ms.

Obi, C.E., Falola, Y., Manikonda, K., et al., 2023. A machine learning approach for gas kick identification. SPE Drill. Complet 38 (4), 663–681. https://doi.org/10.2118/215831-pa.

Osarogiagbon, A.U., Khan, F., Venkatesan, R., et al., 2021. Review and analysis of supervised machine learning algorithms for hazardous events in drilling operations. Process Saf. Environ. Prot. 147, 367–384. https://doi.org/10.1016/j.psep.2020.09.038.

Pandey, Y.N., Rastogi, A., Kainkaryam, S., et al., 2020. Machine Learning in the Oil and Gas Industry. Apress, New York. https://doi.org/10.1007/978-1-4842-6094-4.

Pournazari, P., Ashok, P., van Oort, E., et al., 2015. Enhanced kick detection with low-cost rig sensors through automated pattern recognition and real-time sensor calibration. In: SPE Middle East Intelligent Oil and Gas Conference and Exhibition. SPE-176790-MS. https://doi.org/10.2118/176790-MS.

Sharma, J., Cuny, T., Ogunsanwo, O., et al., 2021. Low-frequency distributed acoustic sensing for early gas detection in a wellbore. IEEE Sens. J. 21 (5), 6158–6169. https://doi.org/10.1109/JSEN.2020.3038738.

Sharma, J., Santos, O.L.A., Feo, G., et al., 2020. Well-scale multiphase flow characterization and validation using distributed fiber-optic sensors for gas kick monitoring. Opt. Express 28 (26), 38773. https://doi.org/10.1364/OE.404981.

Sircar, A., Yadav, K., Rayavarapu, K., et al., 2021. Application of machine learning and artificial intelligence in oil and gas industry. Petrol. Res. 6 (4), 379–391. https://doi.org/10.1016/j.ptlrs.2021.05.009.

Sleiti, A.K., Takalkar, G., El-Naas, M.H., et al., 2020. Early gas kick detection in vertical wells via transient multiphase flow modelling: a review. J. Nat. Gas Sci. Eng. 80, 103391. https://doi.org/10.1016/j.jngse.2020.103391.

Stamnes, O.N., Zhou, J., Kaasa, G.O., et al., 2008. Adaptive observer design for bottomhole pressure of a managed pressure drilling system. In: 2008 47th IEEE Conference on Decision and Control, pp. 2961–2966. https://doi.org/10.1109/CDC.2008.4738845.

Stewart, P.A., Gorman Ng, M., Cherrie, J.W., et al., 2022. Estimation of dermal exposure to oil spill response and clean-up workers after the Deepwater Horizon disaster. Ann. Work Exposures Health 66 (Suppl. 1), i234–i246. https://doi.org/10.1093/annweh/wxab073.

Sule, I.O., Khan, F., Butt, S., 2019. Experimental investigation of gas kick effects on dynamic drilling parameters. J. Pet. Explor. Prod. Technol. 9 (1), 605–616. https://doi.org/10.1007/s13202-018-0510-z.

Sun, X., Sun, B., Zhang, S., et al., 2018. A new pattern recognition model for gas kick diagnosis in deepwater drilling. J. Petrol. Sci. Eng. 167, 418–425. https://doi.org/10.1016/j.petrol.2018.04.035.

Tang, H., Zhang, S., Zhang, F., et al., 2019. Time series data analysis for automatic flow influx detection during drilling. J. Petrol. Sci. Eng. 172, 1103–1111. https://doi.org/10.1016/j.petrol.2018.09.018.

Tost, B.C., Rose, K., Carney, J., et al., 2020. Early kick detection from downhole measurements: A novel method for reducing the frequency and magnitude of loss-of-well-control events. In: Offshore Technology Conference. https://doi.org/10.4043/30831-MS.

Unrau, S., Torrione, P., Hibbard, M., et al., 2017. Machine learning algorithms applied to detection of well control events. In: SPE Kingdom of Saudi Arabia Annual Technical Symposium and Exhibition. SPE 188104–MS. https://doi.org/10.2118/188104-MS.

Verdonck, T., Baesens, B., Óskarsdóttir, M., et al., 2024. Special issue on feature engineering editorial. Mach. Learn. 113 (7), 3917–3928. https://doi.org/10.1007/s10994-021-06042-2.

Wang, J., Ozbayoglu, E., Baldino, S., et al., 2023a. Time series analysis with recurrent neural network for early kick detection. In: Offshore Technology Conference. D021S020R002. https://doi.org/10.4043/32428-MS.

Wang, N., Wang, J., Sun, B., et al., 2016. Study of transient responses in the APWD measurements during gas influx. J. Nat. Gas Sci. Eng. 35, 522–531. https://doi.org/10.1016/j.jngse.2016.08.057.

Wang, Z., Chen, G., Zhang, R., et al., 2023b. Early monitoring of gas kick in deepwater drilling based on ensemble learning method: A case study at South China Sea. Process Saf. Environ. Prot. 169, 504–514. https://doi.org/10.1016/j.psep.2022.11.024.

Wang, Z., Zhao, R., Zang, Y., et al., 2024. Downhole detection of gas kick using low-frequency elastic wave: Multiphysics modeling and its implications. Gas Sci. Eng. 125, 205297. https://doi.org/10.1016/j.jgsce.2024.205297.

Williams, W.C., Taylor, C.E., Almeida, M.A., et al., 2020. Distributed sensing and real time visualization of gas kick dynamics in a full-scale wellbore. In: SPE Annual Technical Conference and Exhibition. https://doi.org/10.2118/201539-MS.

Xu, Y., Guan, Z., Xu, C., et al., 2019. Numerical method and analysis of ultrasonic detection of gas kick in deepwater risers during offshore drilling. Int. J. Heat Mass Tran. 136, 1311–1326. https://doi.org/10.1016/j.ijheatmasstransfer.2019.03.102.

Xu, Y., Yang, J., Hu, Z., et al., 2023. A novel pattern recognition based kick detection method for offshore drilling gas kick and overflow diagnosis. Processes 11 (7), 1997. https://doi.org/10.3390/pr11071997.

Yang, H., Li, J., Liu, G., et al., 2019a. A new method for early gas kick detection based on the consistencies and differences of bottomhole pressures at two measured points. J. Petrol. Sci. Eng. 176, 1095–1105. https://doi.org/10.1016/j.petrol.2019.02.026.

Yang, J., Sun, T., Zhao, Y., et al., 2019b. Advanced real-time gas kick detection using machine learning technology. In: Proceedings of the 29th International Ocean and Polar Engineering Conference (ISOPE), pp. 1404–1409. https://onepetro.org/ISOPEIOPEC/proceedings-abstract/ISOPE19/ISOPE19/ISOPE-I-19-602/21663.

Yin, B., Lin, Y., Wang, Z., et al., 2020a. A gas kick early detection method outside riser based on Doppler ultrasonic wave during deepwater drilling. Petrol. Explor. Dev. 47 (4), 846–854. https://doi.org/10.1016/S1876-3804(20)60100-8.

Yin, Q., Song, Z., Chen, K., et al., 2023. Early warning of deep-water drilling influx based on machine learning. In: Proceedings of the 33rd International Ocean and Polar Engineering Conference, pp. 22–29. https://onepetro.org/ISOPEIOPEC/proceedings-abstract/ISOPE23/ISOPE23/ISOPE-I-23-005/524254.

Yin, Q., Yang, J., Hou, X., et al., 2020b. Drilling performance improvement in offshore batch wells based on rig state classification using machine learning. J. Petrol. Sci. Eng. 192, 107306. https://doi.org/10.1016/j.petrol.2020.107306.

Yin, Q., Yang, J., Tyagi, M., et al., 2021a. Machine learning for deepwater drilling: Gas-kick-alarm classification using pilot-scale rig data with combined surface-riser-downhole monitoring. SPE J. 26 (4), 1773–1799. https://doi.org/10.2118/205365-PA.

Yin, Q., Yang, J., Tyagi, M., et al., 2021b. Field data analysis and risk assessment of gas kick during industrial deepwater drilling process based on supervised learning algorithm. Process Saf. Environ. Prot. 146, 312–328. https://doi.org/10.1016/j.psep.2020.08.012.

Yin, Q., Yang, J., Tyagi, M., et al., 2022. Downhole quantitative evaluation of gas kick during deepwater drilling with deep learning using pilot-scale rig data. J. Petrol. Sci. Eng. 208, 109136. https://doi.org/10.1016/j.petrol.2021.109136.

Yin, Q., Zhu, Q., Song, Z., et al., 2025. Deep learning based early warning methodology for gas kick of deepwater drilling using pilot-scale rig data. Process Saf. Environ. Prot. 196, 106844. https://doi.org/10.1016/j.psep.2025.106844.

Zhang, S., Samuel, R., 2024. Advanced real-time early kick and loss detection through a hybrid data-driven and physics-constrained approach. In: SPE Western Regional Meeting. https://doi.org/10.2118/218837-MS.

Zhang, G., Yang, H.W., Li, J., et al., 2025a. Numerical simulation of gas kick evolution and wellbore pressure response characteristics during the deepwater dual gradient drilling. Pet. Sci. 22 (1), 398–412. https://doi.org/10.1016/j.petsci.2024.12.010.

Zhang, Z., Yin, X., Sun, C., et al., 2025b. Gas kick monitoring in deep-water drilling risers based on ultrasonic Doppler spectroscopy. Ocean Eng. 321, 120457. https://doi.org/10.1016/j.oceaneng.2025.120457.

Zhang, Z., Yin, X., Sun, C., et al., 2026. Research on gas kick identification and quantification algorithm in deep-water drilling based on multiscale fuzzy diversity entropy. Process Saf. Environ. Prot. https://doi.org/10.1016/j.psep.2026.108417.

Zhou, G., Leach, C., Denduluri, V.S., et al., 2021. Pressure-difference method for gas-kick detection in risers. SPE J. 26 (5), 2479–2497. https://doi.org/10.2118/205362-PA.

Zhu, Z., Han, G., Liang, X., et al., 2024. Rapid classification and diagnosis of gas wells driven by production data. Processes 12 (6), 1254. https://doi.org/10.3390/pr12061254.