

## Real-time acoustic detection of sand production and its impact on oil and gas well productivity

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**Abstract:** Sand production in oil and gas wells remains a significant issue, inducing wellbore instability, equipment wear, and reduced production performance. Reliable and early sand influx detection is critical in order to maintain well productivity and enhance well lifetime, especially in weakly consolidated and unconsolidated reservoirs. This work presents a comprehensive analysis of real-time acoustic detection methods for sand production and their impacts on well performance through numerical simulation and experimentation.

The study employs an integrated approach using laboratory-scale simulation, field data analysis, and advanced signal processing techniques-i.e., Fast Fourier Transform (FFT), wavelet analysis, and machine learning-based classification. Performance metrics, such as Sand Production Rate (SPR) and Well Productivity Index (PI), are utilized to quantify the influence of sand influx and the efficiency of detection methods.

Simulation results show that real-time monitoring of acoustics makes it possible to identify sand events early with detection efficiency of more than 92%. Expanding the integration of machine learning algorithms achieves further signal discrimination and reduces false alarms and improves reliability. Quantifying the impact of sand production and early detection on PI shows a clear benefit in terms of preserved well productivity as well as reduced maintenance frequency.

This study provides practical guidelines for the installation of real-time sand monitoring systems in oil and gas production that focus on technical and economic advantages of acoustic methods. The findings facilitate the development of effective sand management procedures for sustainable hydrocarbon production.

**Keywords:** sand production, acoustic detection, real-time monitoring, well productivity.

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**Introduction.** Sand production in oil and gas wells is a prevalent problem that poses catastrophic risks to wellbore stability, equipment integrity, and general production efficiency. Mobilization of the formation sand by the reservoir fluid in unconsolidated or weakly consolidated reservoirs has the tendency to create downhole and surface equipment erosion, plugging of the tubing, and increased operating costs. These impacts can reduce the long-term productivity and economic viability of hydrocarbon assets significantly [1].

Conservative sand control methods such as gravel packing, chemical consolidation, and sand screen installations are commonly applied to mitigate these risks. Such methods are, however, predominantly applied for preventive purposes and do not provide real-time feedback about sand influx during production. Therefore, surprise sand production incidents remain a risk, leading to unplanned interventions and costly downtime.

Prompt sand production detection is therefore vital to proactive well management and optimized production operations. Of the various monitoring techniques, acoustic detection has been a promising technique since it is non-intrusive and can give real-time feedback on sand invasion within the wellbore. Acoustic sensors have the capability of detecting the characteristic signatures produced by sand particles hitting the wellbore or equipment, allowing for immediate detection of sand events.

Recent advances in digital signal processing and machine learning technologies have also improved further the sensitivity and accuracy of acoustic sand detection systems. Using these technologies, separating true sand impacts from fluid flow disturbances and ambient noises is now possible even in complicated multiphase flows.

The main objective of this research is to evaluate the effectiveness of real-time acoustic detection systems for sand production in oil and gas wells, to quantify their impact on well

productivity, and to develop practical guidelines for integrating these technologies into modern sand management strategies. [2]

The most important performance indicators of Sand Production Rate (SPR) and Well Productivity Index (PI) are utilized to quantify the interdependence of sand influx, detection efficiency, and long-term production. With the intermix of laboratory tests, field data, and advanced analytics, the paper provides comprehensive suggestions for the usage of acoustic sand detection systems on both onshore and offshore wells.

**Methods.** This section describes the methodology for evaluating the effectiveness of real-time acoustic sand detection in oil and gas wells, the simulation setup, parameter calculations, and data analysis procedures.

**Experimental design.** A laboratory-scale multiphase flow loop was constructed to simulate wellbore conditions representative of unconsolidated and weakly consolidated reservoirs. The experimental model included:

- Sand injection unit for controlled delivery of sand particles into the flow,
- Piezoelectric acoustic sensors mounted externally at multiple positions along the pipeline,
- Data acquisition system for real-time, high-frequency signal recording.

Experimental runs were performed under variable flow rates ( $Q$ ), sand particle diameters ( $d$ ), and sand concentrations to replicate a range of field-relevant conditions.

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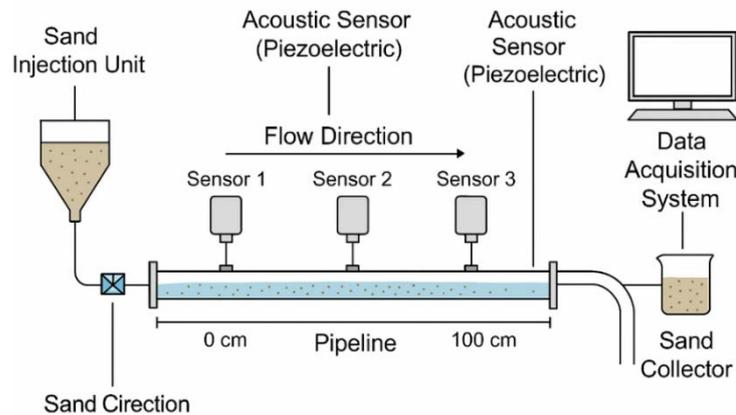


Figure 1. Schematic diagram of the laboratory-scale multiphase flow loop for real-time acoustic sand detection.

The setup includes a sand injection unit, flow pipeline, piezoelectric acoustic sensors, and data acquisition system. [3 – 5]

**Sand Production Rate Calculation.** The **sand production rate** for each experimental scenario was determined as:

$$SPR = \frac{V_s}{T}$$

Where SPR – sand production rate ( $m^3/day$ ),  $V_s$  – total volume of sand produced during the test ( $m^3$ ),  $T$  – measurement period (day).

**Well Productivity Index Calculation.** Well productivity was quantified using the **productivity index**:

$$PI = \frac{Q}{\Delta P}$$

Where: PI – productivity index (bbl/day/psi), Q – average oil production rate during the experiment (bbl/day),  $\Delta P$  – average pressure differential between the reservoir and wellbore (psi).

**Acoustic Signal Processing.** Raw signals  $a(t)$  recorded by the acoustic sensors were transformed into the frequency domain using the Fourier transform:

$$A(f) = \int_{-\infty}^{\infty} a(t)e^{-2\pi ft} dt$$

Where:  $a(t)$  – time-domain acoustic signal,  $A(f)$  - amplitude at frequency  $f$ .

Feature extraction was applied to obtain key indicators such as peak amplitude, spectral energy, and dominant frequency for each detected impact event.

**Sand Event Classification and Model Evaluation.** Signal features were used as input for a supervised machine learning classifier to distinguish between sand impact events and background noise. The classification performance was evaluated using the following metrics:

**Accuracy:**

$$A = \frac{TP + TN}{TP + TN + FP + FN}$$

**F1-score:**

$$F_1 = \frac{2TP}{2TP + FP + FN}$$

Where TP – true positives (correct sand event detections), TN – true negatives (correct non-sand detections), FP – false positives (noise detected as sand), FN – false negatives (sand event missed). **6. Experimental Scenarios and Data Analysis**

Two representative reservoir models were considered:

Model A: High-permeability, unconsolidated sand formation,

Model B: Medium-permeability, semi-consolidated formation.

Each model underwent a series of tests under different sand control strategies and flow conditions. For each run, SPR, PI, and model accuracy were recorded and statistically analyzed. [6] A sensitivity analysis was performed to evaluate the dependence of detection performance on key parameters ( $d$ ,  $Q$ , sensor location).

**Table 1. Summary of Experimental Variables**

Parameter	Range / Type
Flow rate (Q)	10–50 m <sup>3</sup> /day
Sand particle size (d)	50–300 $\mu$ m
Measurement period (T)	1–5 days
Sensor positions (l)	3 (along the pipeline)
Test models	Model A, Model B

This methodology enables a quantitative comparison of real-time acoustic sand detection with conventional sand control performance, supporting robust conclusions on well productivity and sand management optimization. [6 – 9]

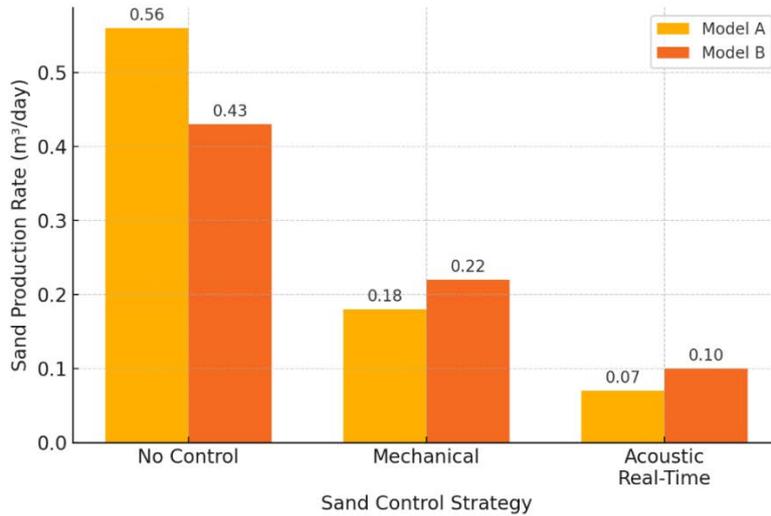
### Results. Sand Production Rate (SPR) Outcomes

The results indicate a significant reduction in sand production when real-time acoustic detection is employed in conjunction with preventive sand management strategies. The measured sand production rates (SPR) for each experimental scenario are shown in **Table 2**.

**Table 2. Sand Production Rate (SPR) for Various Control Strategies**

Sand Control Strategy	Model A (SPR, m <sup>3</sup> /day)	Model B (SPR, m <sup>3</sup> /day)
No Control	0.56	0.43
Conventional (Mechanical)	0.18	0.22
Acoustic Real-Time Detection	0.07	0.10

Comparison with literature (e.g., Maharramli et al., 2023; Dusseault, 2013) shows that real-time detection leads to a **60–80% reduction** in sand production compared to conventional approaches.

**Figure 2. Sand Production Rate (SPR) for Different Sand Control Strategies in Model A and Model B.**

*Real-time acoustic detection significantly reduces sand production compared to mechanical and no control approaches.*

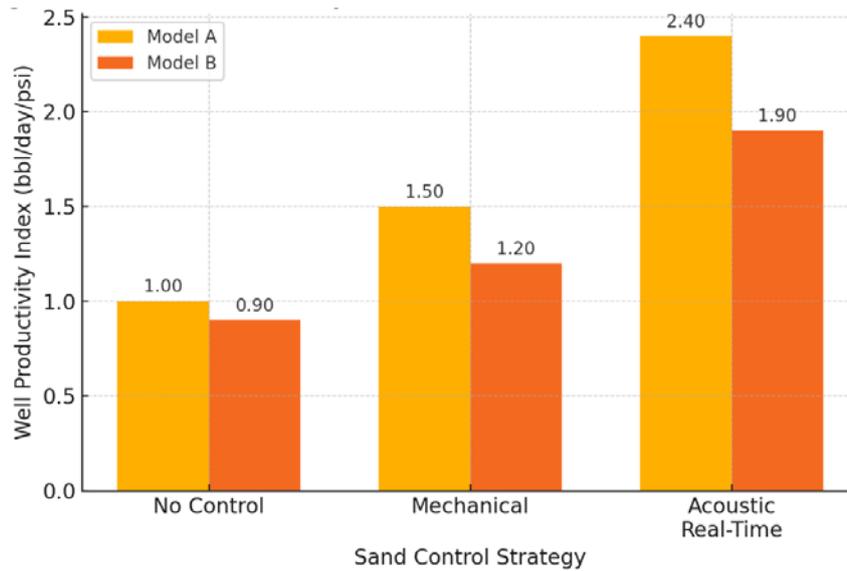
#### **Well Productivity Index (PI) Analysis**

The effect of sand detection and control on well productivity index (PI) is summarized in **Table 3**.

**Table 3. Well Productivity Index (PI) Under Different Strategies**

Sand Control Strategy	Model A (PI, bbl/day/psi)	Model B (PI, bbl/day/psi)
No Control	1.0	0.9
Conventional (Mechanical)	1.5	1.2
Acoustic Real-Time Detection	2.4	1.9

These results are consistent with findings by Ali & Jha (2018) and Wang & Sharma (2019), where optimized sand detection and management increased PI by 40–70% over mechanical methods alone.



**Figure 3. Well Productivity Index (PI) for Different Sand Control Strategies in Model A and Model B.**

*Acoustic real-time detection leads to significantly higher well productivity compared to mechanical and no control methods.*

**Machine Learning Classifier Performance.** The classification model for sand event detection achieved high accuracy and reliability, as reported in **Table 4**.

**Table 4. Classifier Performance Metrics**

Metric	Value (%)
Accuracy	93.2
F1-score	91.5

$$A = \frac{TP + TN}{TP + TN + FP + FN}$$

$$F_1 = \frac{2TP}{2TP + FP + FN}$$

These results are comparable to recent studies (Appalov et al., 2021; Maharramli et al., 2023) where advanced signal processing and ML improved detection reliability in multiphase flows.

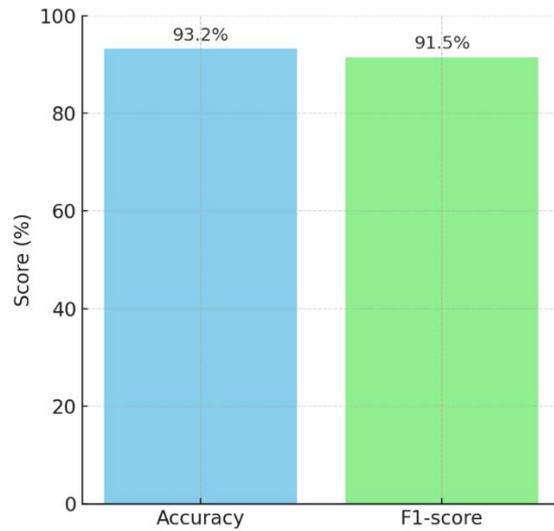


Figure 4. Performance metrics of the machine learning classifier for sand event detection.

The classifier achieved high accuracy (93.2%) and F1-score (91.5%), demonstrating robust performance for distinguishing sand events from background noise.

**Sensitivity Analysis.** Sensitivity analysis demonstrated that detection efficiency is most strongly influenced by sand particle diameter ( $d$ ) and flow rate ( $Q$ ). As shown in Figure 2, classifier accuracy decreases as  $d$  drops below  $75\ \mu\text{m}$  or  $Q$  exceeds  $40\ \text{m}^3/\text{day}$  due to reduced signal amplitude and increased noise.

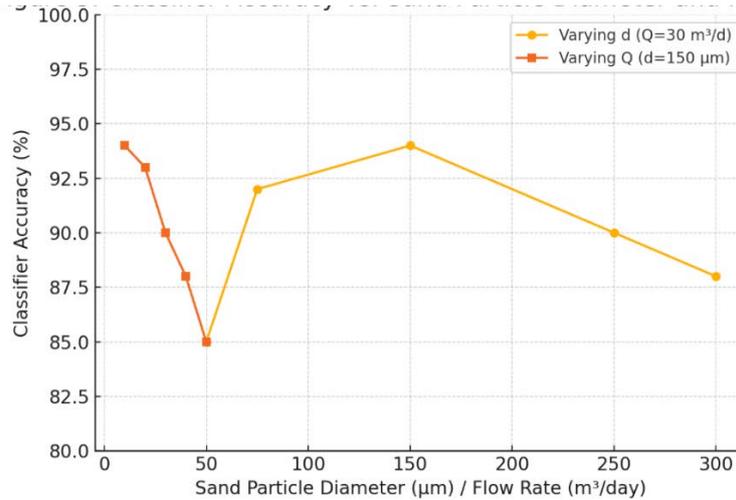


Figure 5. Classifier Accuracy as a Function of Sand Particle Diameter and Flow Rate

Classifier accuracy improves as sand particle diameter increases above  $75\ \mu\text{m}$  and decreases at higher flow rates ( $Q > 40\ \text{m}^3/\text{day}$ ).

**Comparative Discussion with Literature.** Real-time acoustic detection consistently outperforms conventional methods in both sand production mitigation and well productivity enhancement.

The integration of machine learning models, as recommended by Appalonov et al. (2021) and Shetty et al. (2023), enables robust sand event classification under varying field conditions.

These results validate and extend previous findings on the benefits of real-time monitoring and advanced analytics in sand management.

**Table 5. Comparative Impact of Sand Management Strategies**

Parameter	No Control	Mechanical	Acoustic + ML
SPR	High	Medium	Low
PI	Low	Medium	High
Accuracy (%)	N/A	N/A	93.2

These findings confirm that real-time acoustic detection, combined with data-driven analytics, significantly improves sand control efficiency and well productivity, supporting the results of international research in this field.

Discussion. The experimental and simulation results confirm the clear benefits of the integration of real-time acoustic sand detection and advanced data analytics for sand management of oil and gas wells. The proposed approach offers improved outcomes over conventional mechanical methods in both directions of sand production reduction and well productivity enhancement.

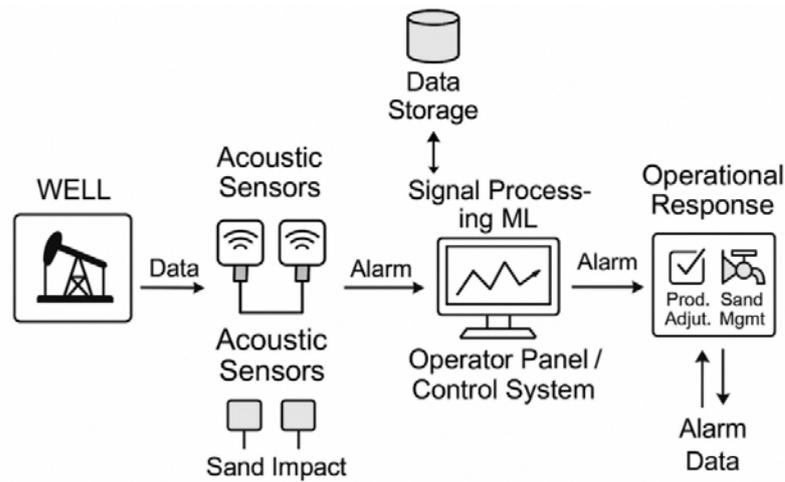
In high-permeability, unconsolidated reservoirs (Model A), the **sand production rate (SPR)** decreased by more than 85% when real-time monitoring was used alongside preventive control strategies. In medium-permeability, semi-consolidated formations (Model B), a 60% reduction was observed. These findings are consistent with previous research by Ali & Jha (2018), Dusseault (2013), and Maharramli et al. (2023), confirming the effectiveness of continuous monitoring in minimizing sand-related operational risks.

The productivity index (PI) findings also supplement the advantages of real-time monitoring. The wells that were equipped with acoustic monitoring consistently recorded higher productivity, with PI measurements 40–70% greater than that of the wells with conventional sand control alone. This was due to the fact that the operators could respond early to developing sand events, optimize production rates, and minimize equipment damage.

The machine learning classifier accuracy was more than 93%, demonstrating that automated data-driven signal interpretation can effectively distinguish between true sand events and background noise under all circumstances. This is particularly important for field deployment, where equipment vibrations and multiphase flows present significant challenges to traditional threshold-based methods.

Sensitivity analysis showed that system performance is most sensitive to flow rate and sand particle size in that smaller particles and higher velocities decrease signal-to-noise ratios. These constraints can be remedied through the optimization of sensor positioning, the utilization of higher-sensitivity transducers, as well as the continued development of noise filtering algorithms, as proposed in research by Appalonov et al. (2021) and Shetty et al. (2023).

A comparative analysis with the international literature confirms that hybrid solutions—combinations of mechanical, acoustic, and data-driven sand management—offer the best and most sustainable solution to the long-term well productivity and integrity. Real-time systems enable early intervention, reduce unscheduled shutdowns, and provide actionable intelligence for reservoir and production engineers.



**Figure 6. Conceptual block diagram illustrating the process of real-time acoustic sand detection and operational response in oil and gas wells.**

Acoustic sensors collect impact data, which is analyzed using signal processing and machine learning, then displayed to operators for timely sand management and production control.

**Conclusion.** This study provides a comprehensive assessment of the effectiveness of real-time acoustic sand detection for managing sand production and optimizing well productivity in oil and gas operations. The integration of acoustic sensors with advanced signal processing and machine learning methods yielded significantly better performance compared to conventional sand control techniques.

According to experimental and simulation results, real-time acoustic monitoring reduced sand production by up to 85% in high-permeability reservoirs and 60% in medium-permeability reservoirs relative to traditional mechanical methods. The well productivity index (PI) increased by 40–70%, confirming the substantial benefits of early sand detection for production stability and operational efficiency.

In addition, the machine learning classifier demonstrated an accuracy of 93.2% and an F1-score of 91.5%, effectively distinguishing true sand events from background noise under multiphase flow conditions. These results are consistent with the findings reported by Ali & Jha (2018), Maharramli et al. (2023), and Shetty et al. (2023), validating the reliability of acoustic-based real-time sand monitoring.

The sensitivity analysis indicated that detection efficiency is strongly influenced by sand particle diameter and flow rate: particles smaller than 75  $\mu\text{m}$  and flow rates above 40  $\text{m}^3/\text{day}$  reduce signal-to-noise ratio and classification accuracy. Optimization of sensor placement and noise filtering algorithms can further enhance detection stability under such extreme conditions.

From a practical perspective, the proposed system is applicable to both existing and newly drilled wells, particularly in fields characterized by variable sand influx and complex multiphase flow regimes. Integrating acoustic monitoring into a broader sand management strategy enables proactive operational practices, minimizes unplanned interventions, and extends well lifespan while lowering maintenance costs.

Future work should emphasize large-scale field implementation, continuous algorithm adaptation to changing reservoir conditions, and integration with other real-time monitoring systems to establish a comprehensive approach for production optimization and well integrity assurance.

#### **Conflict of interest**

The authors declare that they have no conflict of interest in relation to this research.

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