



Published by Avanti Publishers
**International Journal of Petroleum
Technology**

ISSN (online): 2409-787X



Distributed Acoustic Sensing for Monitoring Oil-Water Two-Phase Flow in Horizontal Wells: Experimental Characterization and Flow-Velocity Modeling

Yixin Zhang, Hongwen Luo*, Sihang Xie, Tingting Zhou, Haitao Li, Yang Zhang,
Xinhan Feng, Yiming Ren, Weilin Chen and Kaiyi Jia

Southwest Petroleum University, Chengdu 610500, China

ARTICLE INFO

Article Type: Research Article

Academic Editor: Rouholah Ahmadi

Keywords:

Horizontal well

Acoustic energy

Oil-water two-phase flow

Average wellbore velocity

Distributed acoustic sensing

Timeline:

Received: July 23, 2026

Accepted: September 21, 2026

Published: October 09, 2026

Citation: Zhang Y, Luo H, Xie S, Zhou T, Li H, Zhang Y, Feng X, Ren Y, Chen W, Jia K. Distributed acoustic sensing for monitoring oil-water two-phase flow in horizontal wells: Experimental characterization and flow-velocity modeling. *Int J Pet Technol.* 2026; 13(2): 73-88.

DOI: <https://doi.org/10.15377/2409-787X.2026.13.6>

ABSTRACT

Distributed acoustic sensing (DAS) enables continuous acquisition of acoustic responses along a wellbore and has considerable potential for production-profile monitoring and flow-state identification in horizontal wells. However, existing studies have focused mainly on correlations between DAS signal characteristics and flow states, while the coupled effects and quantitative relationships among fluid properties, wellbore conditions, and DAS responses remain insufficiently understood. To characterize DAS responses under oil-water two-phase flow, physical simulation experiments were conducted in a horizontal wellbore under different crude-oil viscosities, water cuts, and wellbore inclinations. Spectral characteristics and acoustic-energy variations were analyzed to determine how fluid properties and wellbore conditions affect DAS responses. The results show that the dominant DAS frequency shifts overall toward lower frequencies as crude-oil viscosity increases; DAS acoustic energy generally increases with water cut within the investigated oil-water two-phase conditions; and both spectral and energy responses vary markedly with wellbore inclination. On this basis, an exponential relationship between DAS acoustic energy and average wellbore velocity was established, followed by a multifactor response-surface model incorporating average wellbore velocity, crude-oil viscosity, water cut, and wellbore inclination. The standardized regression results identify average wellbore velocity as the primary factor affecting DAS acoustic energy and indicate coupling between average wellbore velocity and both water cut and crude-oil viscosity. These results provide an experimental basis for DAS-based interpretation of flow parameters and production profiles in horizontal wells.

*Corresponding Author

Email: rojelhwa@163.com

1. Introduction

Distributed acoustic sensing (DAS) is a distributed sensing technique that enables continuous acoustic monitoring by detecting variations in Rayleigh backscattered light. Compared with conventional point sensors, DAS offers high spatial resolution, real-time monitoring, long sensing distance, and adaptability to complex downhole environments, allowing continuous acquisition of dynamic acoustic responses along the fiber. With advances in fiber-optic sensing and signal-processing methods, DAS has been increasingly applied to dynamic oil and gas well monitoring, hydraulic-fracturing evaluation, well-integrity diagnostics, and production-profile interpretation, providing a new means of identifying wellbore flow states and obtaining flow parameters under complex conditions [1-3].

For DAS-based flow-rate monitoring and multiphase-flow analysis, Johannessen *et al.* [4] determined wellbore flow rates through rapid processing of DAS acoustic signals. Daley *et al.* [5] used DAS for dynamic monitoring of subsurface media. Xing *et al.* [6] investigated gas-liquid two-phase flow under conventional and reverse gas-lift conditions and analyzed the effects of gas and liquid volumetric flow rates and gas-injection mode on pressure drop and liquid holdup. Liu *et al.* [7] analyzed the possible flow regimes in horizontal wellbores on the basis of multiphase-flow theory and developed a pressure model for gas-liquid two-phase flow in horizontal wells. He [8] applied DAS to offset-well monitoring during shale-gas fracturing and demonstrated its advantages in real-time monitoring and timely adjustment of fracturing parameters. He *et al.* [9] conducted real-time monitoring with fiber installed outside the casing in a shale-gas horizontal well in southern Sichuan and used DAS signal characteristics to identify two types of channeling/leakage behavior and diagnose fracture propagation.

For water-cut identification and production-profile characterization, Liu *et al.* [10] combined wavelet time-scattering transforms with short-time Fourier transforms to extract low-variance scattering and time-frequency features, improving the classification accuracy of water-cut ranges. Oil-water two-phase flow in horizontal pipes, however, is jointly affected by viscosity ratio, water cut, flow velocity, and pipe inclination through their effects on flow regime, interfacial fluctuations, and phase interaction [11, 12]. DAS responses therefore need to be interpreted together with the underlying oil-water flow behavior. Zharnikov *et al.* [13] developed a coupled numerical model of acoustic propagation and fiber-strain response and clarified the influence of DAS gauge length on leak-location accuracy. Their frequency-band energy (FBE) approach separated leak signals from formation and wellbore noise and improved leak-detection stability under complex conditions. Deng *et al.* [14] proposed a two-stage strategy consisting of rapid and refined processing: Fourier transforms were used for rapid frequency-band energy extraction, while piecewise polynomial detrending, Gaussian-convolution smoothing, and improved wavelet-threshold denoising were used to enhance low-frequency resolution. Fidaner *et al.* [15] proposed a real-time wavelet-transform and artificial-neural-network (ANN) method in which wavelet-based feature extraction reduces computational cost and the ANN estimates flow rate and flow regime from the extracted features. Hu *et al.* [16] developed a model and workflow for field liquid-production profiling, using frequency analysis to determine the effective DAS band and acoustic energy to calculate the production profile. Luo *et al.* [17] conducted physical simulation experiments of oil-water two-phase flow in a horizontal well and examined the relationship between DAS responses and flow states, providing an experimental basis for DAS-based monitoring of horizontal-well two-phase flow.

For DAS signal processing, Xiao *et al.* [18] proposed several analysis techniques, including root-mean-square acoustic-energy analysis, amplitude estimation, and flow-based sound-speed determination. A two-dimensional Fourier transform was applied to DAS data acquired in a producing well to convert time-space-domain data into the frequency-wavenumber domain, and a linear-fitting algorithm was then used to determine the acoustic velocity of the wellbore fluid. Shirdel *et al.* [19] combined DAS spectral analysis, DTS and DAS waterfall plots, and steady-state injection analysis to quantitatively interpret injection profiles. Chavarria *et al.* [20] extracted low-frequency DAS components to capture small temperature changes induced by wellbore flow and accurately locate casing-annulus leaks. Hashish *et al.* [21] combined time- and frequency-domain features to characterize flow dynamics and showed that energy normalization and FK filtering can further improve model robustness. Li *et al.* [22] investigated preprocessing and denoising methods for large-volume DAS datasets to improve signal quality. Wavelet analysis and empirical mode decomposition have also been widely used for feature extraction from

nonstationary, noisy, and multiscale signals [23-25]. Related approaches have been applied specifically to DAS data for dynamic feature extraction and signal characterization [26-27].

In summary, substantial progress has been made in DAS-based wellbore-flow monitoring, signal processing, multiphase-flow identification, and production-profile interpretation. However, most existing studies focus on signal-feature identification or flow-parameter inversion under specific operating conditions. Systematic experimental understanding of DAS responses when crude-oil viscosity, water cut, and wellbore inclination vary simultaneously remains limited, and quantitative models capable of representing multifactor coupling are still lacking.

Accordingly, the objective of this study is to systematically characterize DAS spectral and acoustic-energy responses to variations in crude-oil viscosity, water cut, wellbore inclination, and average wellbore velocity, and to establish quantitative models describing their combined effects on DAS acoustic energy. Quantitative relationships between DAS acoustic energy and average wellbore velocity were then established to provide an experimental basis for DAS-based production-profile interpretation and flow-parameter estimation in horizontal wells. The remainder of this paper is organized as follows. Section 2 describes the experimental setup and experimental design. Section 3 presents the DAS data-processing procedure. Section 4 discusses the experimental response characteristics, regression analysis, and multifactor response-surface model. Section 5 summarizes the main conclusions.

2. Experimental Design

2.1. Experimental Setup

The experimental setup is shown in Fig. (1) and consists of four main modules: an acoustic-monitoring module, a horizontal-wellbore module, a fluid-injection module, and a waste-fluid recovery module. The modules are connected in sequence. The acoustic-monitoring module includes an acoustic source, a signal-acquisition terminal, and an armored optical fiber. The horizontal-wellbore module consists of a perforated tube, casing, and sealing connectors. The casing is 24 m long, with one radial inflow point every 6 m. Multiple vertical holes are uniformly distributed along the casing to connect the inside and outside of the wellbore. The perforated tube is installed inside the casing, leaving an annular space between the tube and casing. A single-mode armored optical fiber with an outer diameter of 6.35 mm is deployed inside the casing to simulate field deployment in which fiber is conveyed into the well by coiled tubing. The fluid lines are high-temperature-, high-pressure-, and corrosion-resistant hydraulic hoses. Reducer threaded connections are used between the lines and the horizontal wellbore, fluid-supply system, and waste-fluid recovery system to prevent leakage at the connections under elevated internal pressure.

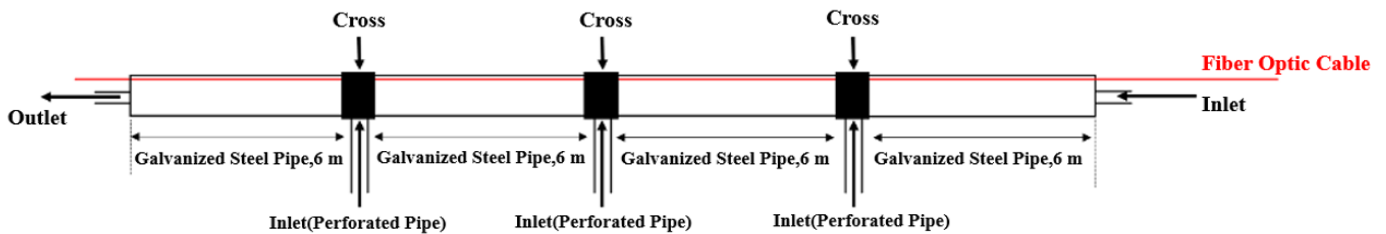


Figure 1: Schematic of the horizontal-well experimental setup.

2.2. Experimental Design

To investigate variations in DAS response under different flow conditions, crude-oil viscosity, water cut, and wellbore inclination were selected as the principal experimental variables. By varying these parameters, DAS spectral characteristics and acoustic-energy responses were obtained under different conditions, and quantitative relationships between DAS response parameters and average wellbore velocity were subsequently established. The experimental matrix is listed in Table 1.

Table 1: Experimental matrix for DAS responses to oil-water two-phase inflow in a horizontal well.

No.	Crude-oil Viscosity (mPa·s)	Inclination	Wellbore Flow Rate (L/min)	Water Cut
1	3	-15°, 0°, +15°	0.01-1	0-90%
2	10			
3	60			
4	/	0°	0.01-1	100%

3. Data Processing

Distributed acoustic sensing (DAS) is based on phase-sensitive optical time-domain reflectometry (Φ -OTDR), in which phase variations in Rayleigh backscattered light are analyzed to obtain distributed dynamic-strain information along the optical fiber [28]. DAS data are large in volume, nonstationary, and susceptible to noise, so time-frequency analysis is required for effective feature extraction. In this study, DAS signals were processed using a fast Fourier transform (FFT) combined with a fourth-order Butterworth low-pass filter [29-31]. Frequency-domain analysis was then used to extract acoustic-response characteristics under different operating conditions and to characterize DAS signals under complex flow conditions [32].

The acquired time-domain DAS signal was transformed into the frequency domain using the discrete Fourier transform [30]:

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-\frac{j2\pi kn}{N}}, k = 0, 1, 2, \dots, N-1 \quad (1)$$

where $x(n)$ is the time-domain signal sequence, $X(k)$ is the complex frequency-domain signal, N is the signal length, and k is the frequency-domain sequence index.

To isolate the frequency band of interest, a Butterworth low-pass filter was applied. Its magnitude-frequency response is given by [29, 33]:

$$|H(j\omega)|^2 = \frac{1}{1 + \left(\frac{\omega}{\omega_c}\right)^{2n}} \quad (2)$$

where n is the filter order, ω_c is the cutoff angular frequency (rad/s), and $H(j\omega)$ is the frequency-response function.

In the digital-filter implementation, the transfer function is expressed as [29, 33]:

$$H(z) = \frac{b_0 + b_1 z^{-1} + \dots + b_M z^{-M}}{1 + a_1 z^{-1} + \dots + a_N z^{-N}} \quad (3)$$

where b_j and a_i are the filter coefficients, M and N are the filter orders, and Z is the transform variable.

Analysis of the measured DAS spectra showed that the principal acoustic response was concentrated within 0-500 Hz. The cutoff frequency was therefore set to 500 Hz, and 0-500 Hz was used as the target band for subsequent acoustic-energy analysis.

The root-mean-square (RMS) value was used as an indicator of DAS acoustic energy [34]:

$$E_{\text{RMS}} = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2} \quad (4)$$

where x_i is the amplitude of the i th sample within the selected frequency band and N is the number of samples in that band.

An example of the processed DAS data is shown in Fig. (2). Fig. (2a) presents the spectrum and Fig. (2b) the corresponding energy spectrum, which can be used to characterize acoustic-energy variations under different operating conditions.

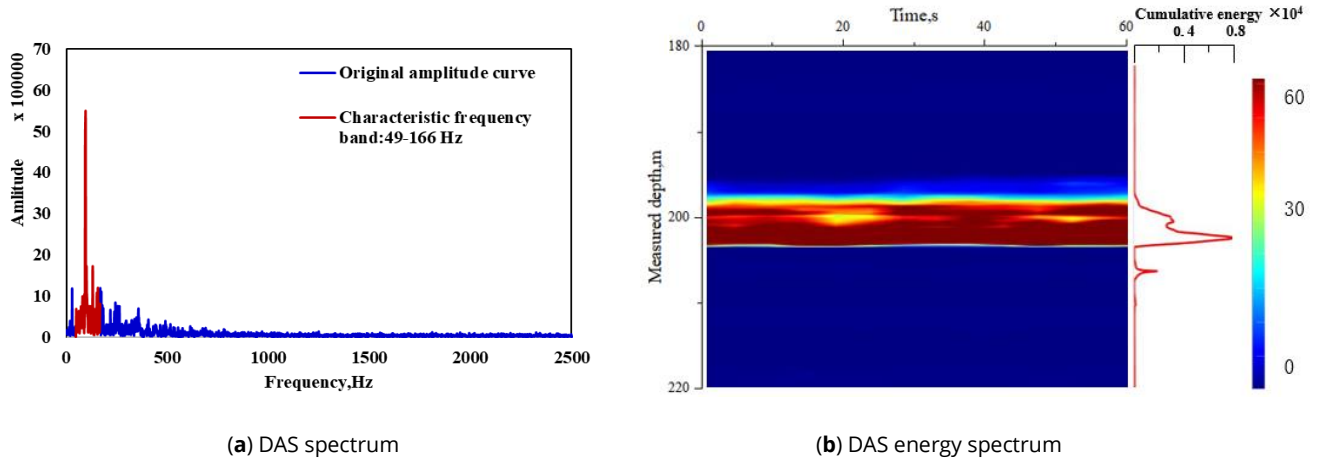


Figure 2: Representative DAS frequency spectrum and corresponding energy spectrum.

4. Results and Discussion

4.1. DAS Response of Two-Phase Flow in a Horizontal Well

4.1.1. Effect of Crude-Oil Viscosity on DAS Response

At a water cut of 0%, an inclination of 0° , and a wellbore flow rate of 1 L/min, DAS responses were measured for crude-oil viscosities of 3, 10, and 60 mPa·s, as shown in Fig. (3). The dominant frequency was 164 Hz at 3 mPa·s,

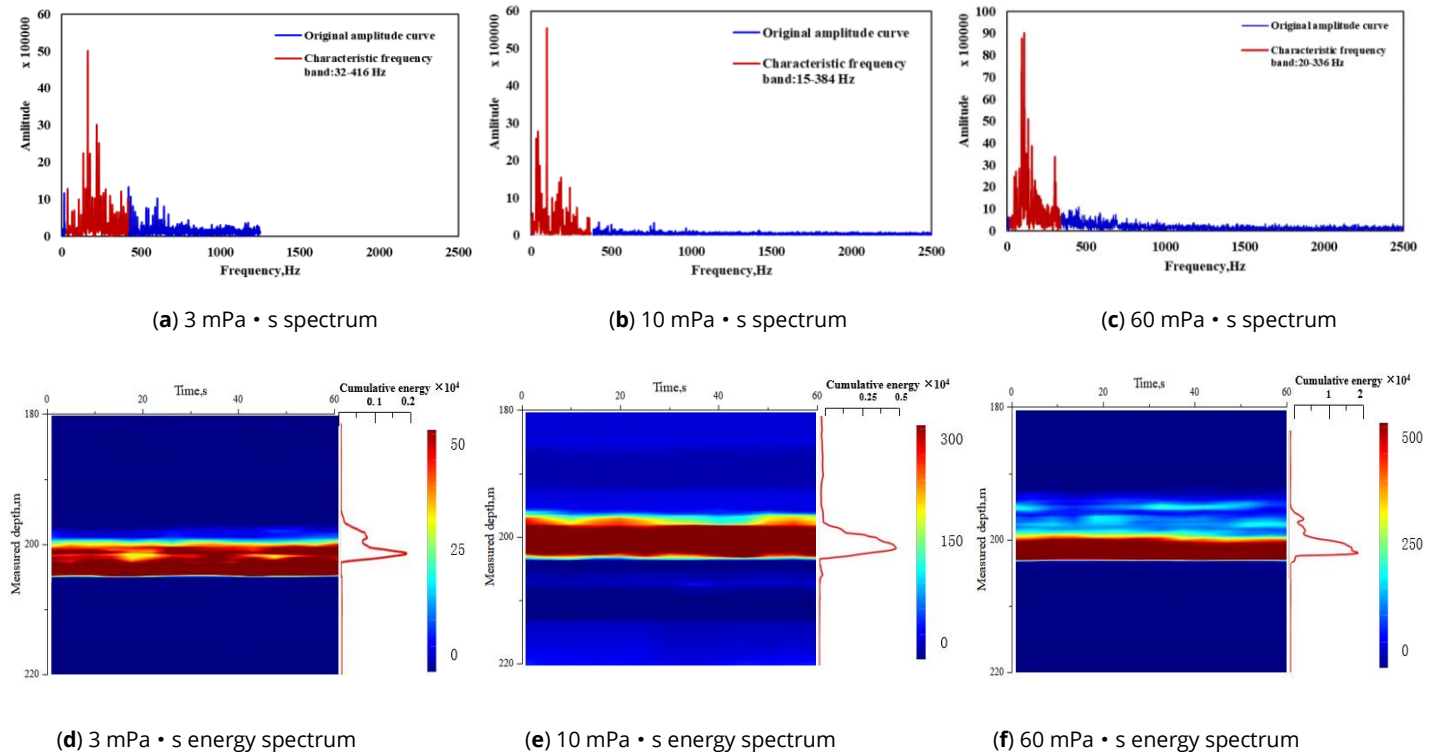


Figure 3: DAS frequency and energy spectra of single-phase oil at different viscosities.

101 Hz at 10 mPa·s, and 94 Hz at 60 mPa·s. The energy spectra further confirmed this trend. As crude-oil viscosity increased, the dominant DAS frequency shifted overall toward lower frequencies, high-frequency components weakened, and the acoustic energy generally increased (Fig. 4). Changes in crude-oil viscosity can modify flow behavior and interfacial characteristics [35], which may in turn affect the DAS spectral and acoustic-energy responses. The systematic shift of the dominant DAS response toward lower frequencies with increasing crude-oil viscosity provides experimental evidence that crude-oil rheological properties are reflected in the acoustic signature of wellbore flow. Under the controlled conditions investigated here, viscosity-dependent changes are manifested simultaneously in the frequency content and acoustic-energy response captured by DAS. This result extends previous DAS flow studies by explicitly demonstrating the sensitivity of DAS spectral characteristics to crude-oil viscosity.

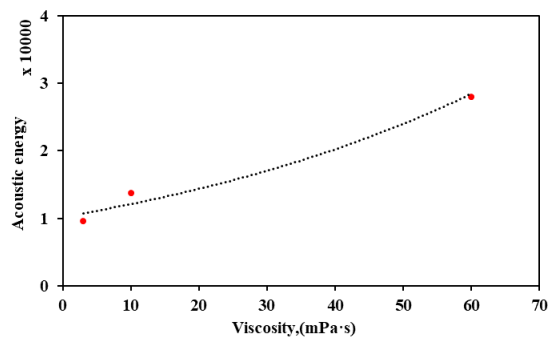


Figure 4: Relationship between crude-oil viscosity and acoustic energy.

4.1.2. Effect of Water Cut on DAS Response

To examine the effect of water cut on DAS response, oil-water two-phase flow experiments were conducted at a crude-oil viscosity of 10 mPa·s, a wellbore inclination of 0 degrees, and a wellbore flow rate of 1 L/min, as shown in Fig. (5). At low water cut, the dominant DAS frequency was approximately 56 Hz and the spectrum exhibited a

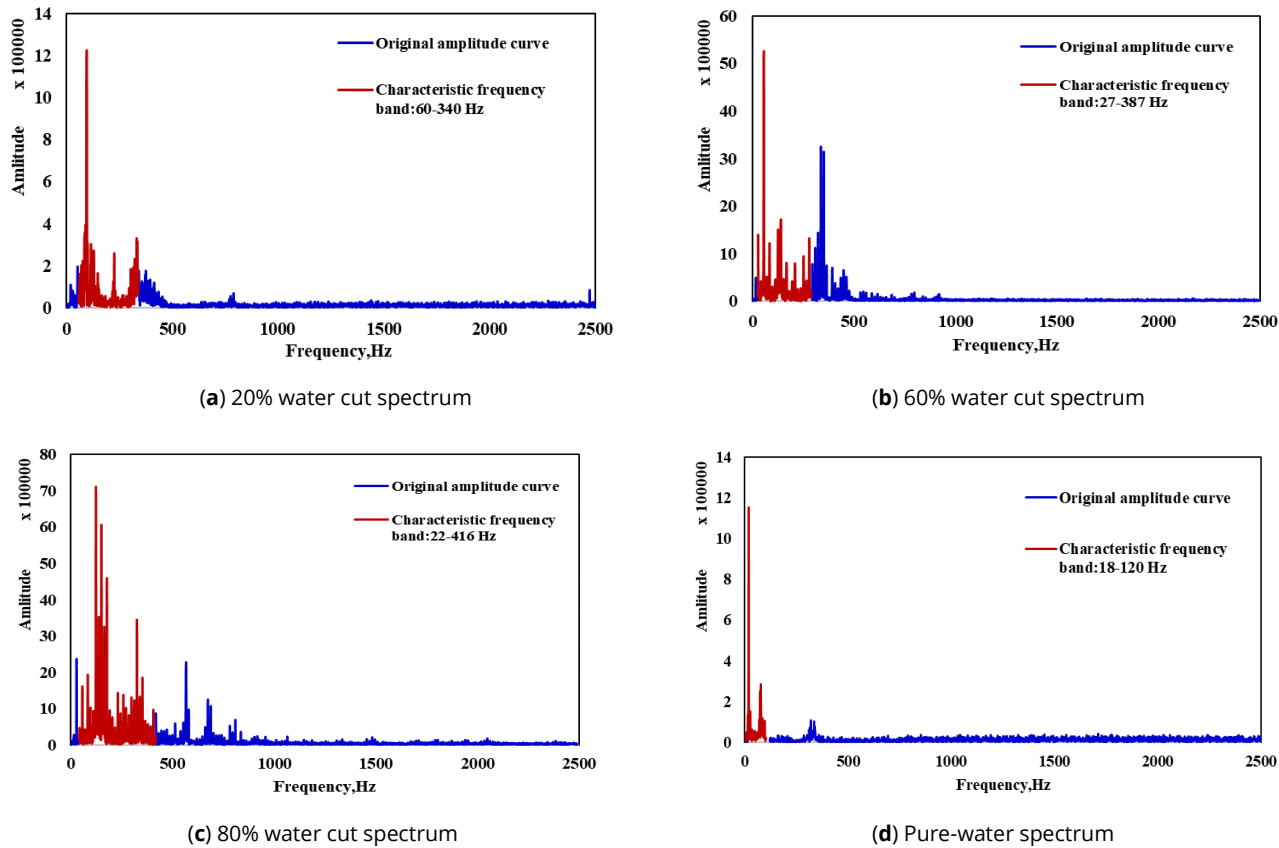
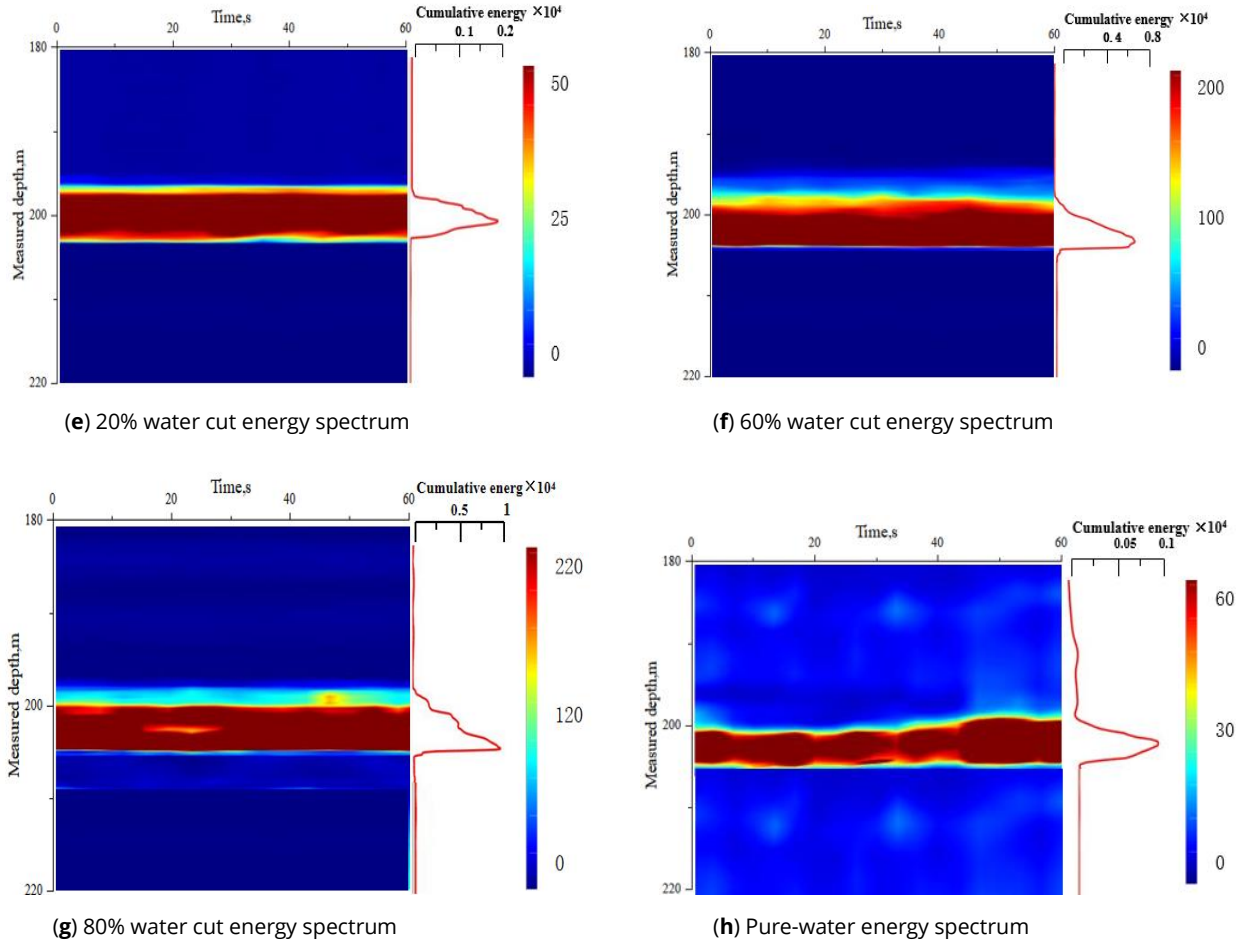
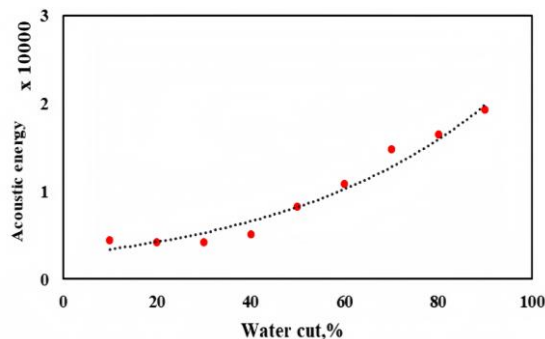


Figure 5 (contd....)

**Figure 5:** DAS spectra and energy spectra under different water-cut conditions and the pure-water control.

concentrated, single-peak narrow-band response. When the water cut increased to 80%, the dominant frequency shifted to 121 Hz, the spectral range broadened markedly, and the contribution of higher-frequency components increased. Fig. (6) further shows that, within the oil-water two-phase conditions, DAS acoustic energy generally increased with water cut and followed a clear exponential trend. This behavior may be associated with changes in phase composition and flow state as water cut increases [36]. The results indicate that DAS response is sensitive not only to flow velocity but also to flow-state differences associated with changes in oil-water composition. The pure-water control exhibited a characteristic frequency range of approximately 18–120 Hz and a lower acoustic-energy level than the high-water-cut two-phase conditions. As an independent single-phase reference, the pure-water result was not included in the exponential fitting.

**Figure 6:** Relationship between water cut and acoustic energy.

4.1.3. Effect of Wellbore Inclination on DAS Response

At a crude-oil viscosity of 10 mPa·s, a water cut of 0%, and a wellbore flow rate of 1 L/min, DAS responses were measured at wellbore inclinations of -15° , 0° , and $+15^\circ$. The spectra show that inclination markedly affects the DAS response. At -15° , the spectrum is concentrated mainly in the low-frequency range; at 0° , the spectral range is broader; and at $+15^\circ$, the response is dominated by low-to-intermediate frequencies. The energy spectra in Fig. (7) show clear differences among the three inclinations, with acoustic energy following the order $+15^\circ > -15^\circ > 0^\circ$. Fig. (8) further indicates that changes in wellbore inclination alter the gravitational contribution and the distribution of flow resistance, thereby affecting the DAS acoustic response. At $+15^\circ$, the component of gravity along the wellbore opposes the flow direction and increases resistance to axial flow. At -15° , the gravitational component acts in the flow direction, producing a force balance different from that under uphill flow. At 0° , the axial component of gravity is nearly zero. These results indicate that inclination changes the axial gravitational component and flow resistance, and differences in force balance among inclinations may be an important cause of the observed variations in DAS acoustic energy. Wellbore inclination should therefore be considered when interpreting horizontal-well flow parameters from DAS data [37, 38].

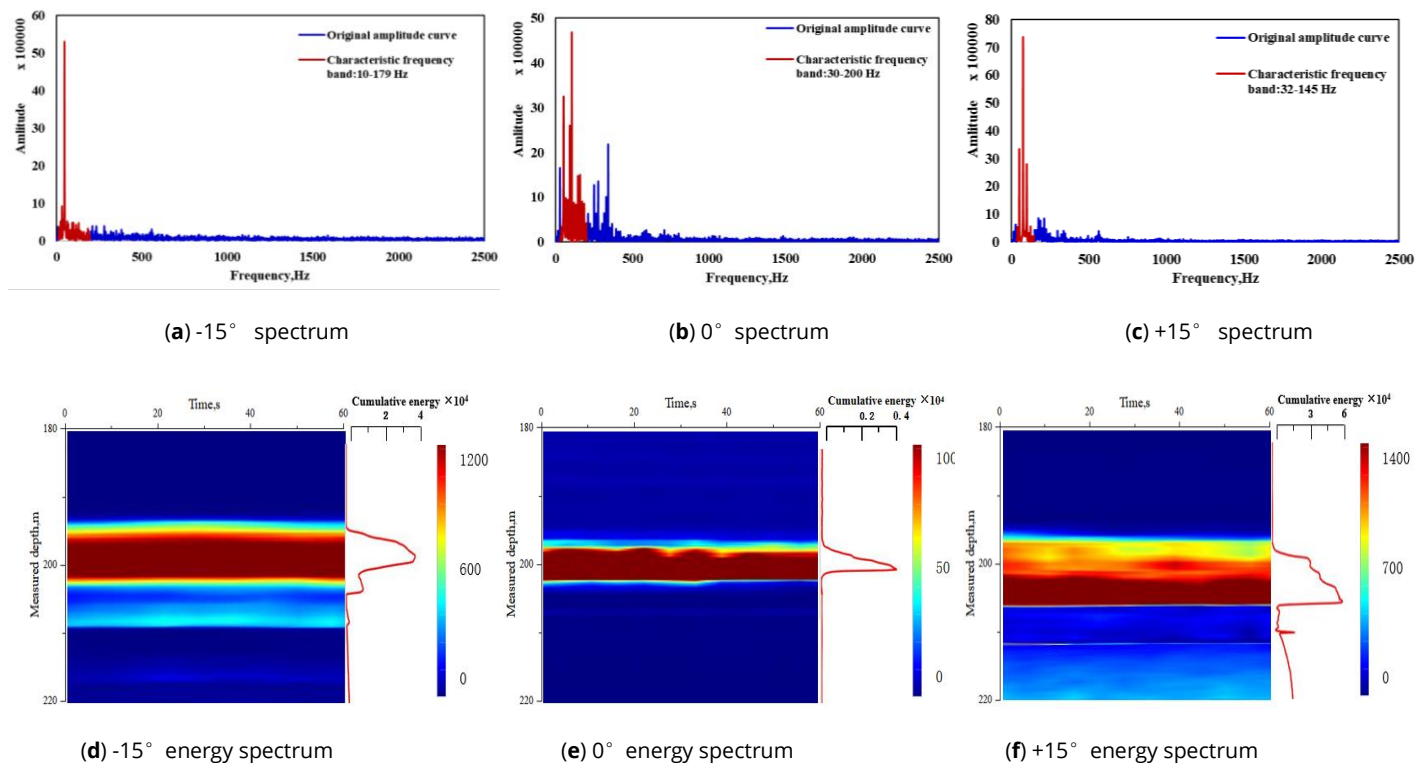


Figure 7: DAS spectra and energy spectra at different wellbore inclinations.

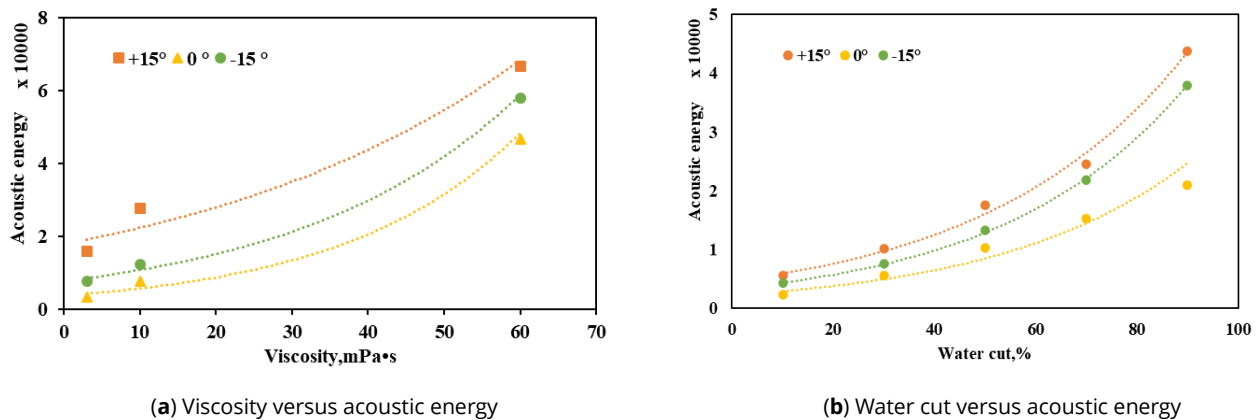
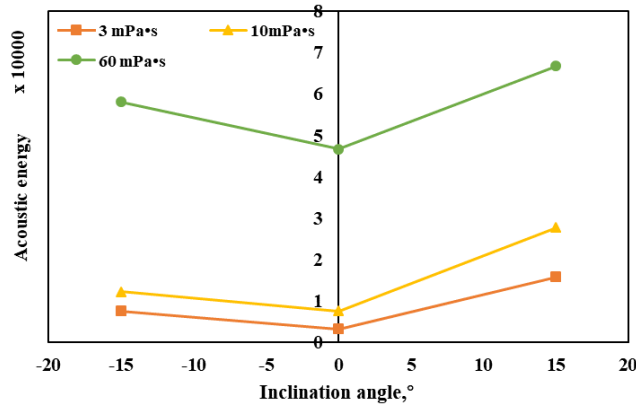
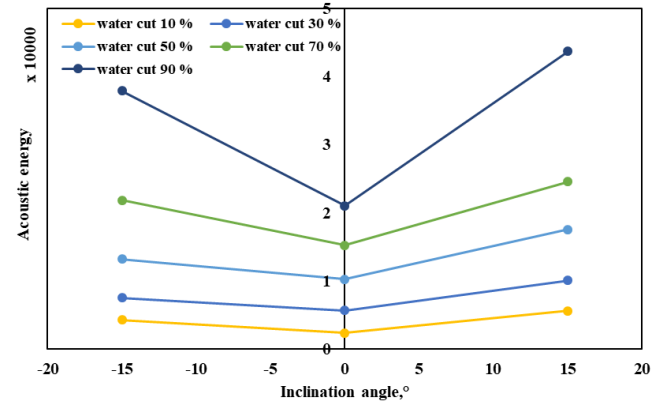


Figure 8 (contd....)



(c) Inclination versus acoustic energy



(d) Inclination versus acoustic energy

Figure 8: Effects of different factors on DAS acoustic energy.

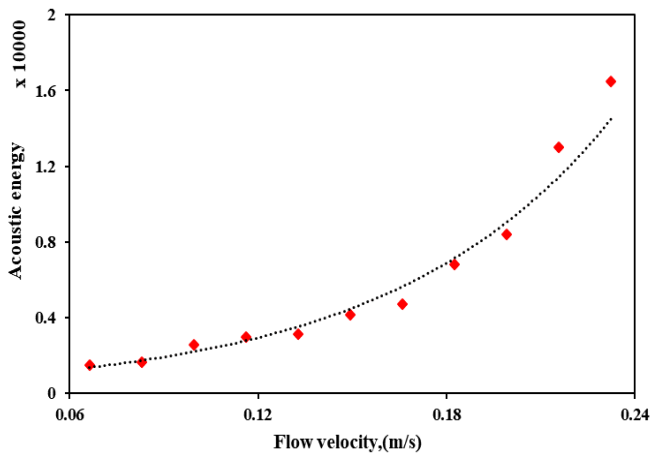
4.2. DAS Response-Velocity Fitting Model for Horizontal-Well with Two-Phase Flow

Average wellbore velocity was used to characterize the overall flow state of the oil–water mixture and was calculated from the effective flow area of the experimental pipe as follows:

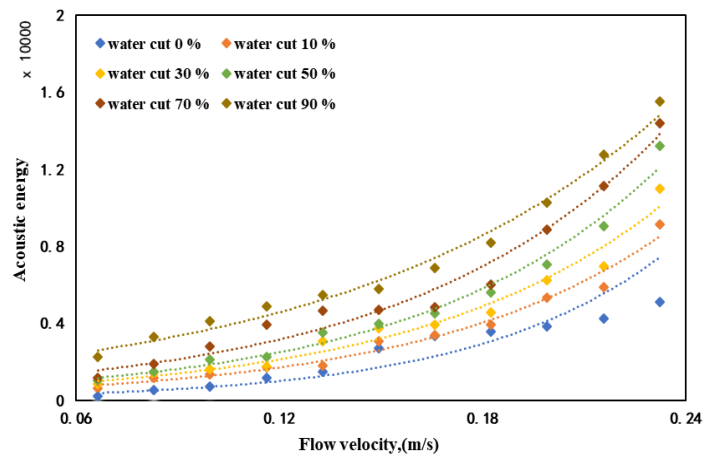
$$v = \frac{Q}{A} \quad (5)$$

where v is the average wellbore velocity (m/s), Q is the volumetric flow rate under the corresponding experimental condition (m³/s), and A is the effective flow area of the experimental pipe (m²).

As shown in Fig. (9–11), DAS acoustic energy generally increases with average wellbore velocity across different crude-oil viscosities, water cuts, and wellbore inclinations, although the magnitude of the increase varies among conditions. This trend is consistent with previous studies showing that DAS measurements are sensitive to wellbore inflow and can be used for flow-parameter analysis [39, 40]. Compared with previous studies that mainly focused on flow-state identification or parameter classification [41–43], the present experiments further quantify how crude-oil viscosity, water cut, and wellbore inclination modify the relationship between DAS acoustic energy and average wellbore velocity. These results indicate that the sensitivity of DAS acoustic energy to average wellbore velocity depends not only on velocity itself but also on fluid properties and wellbore conditions.



(a) Pure water



(b) 3 mPa·s

Figure 9 (contd....)

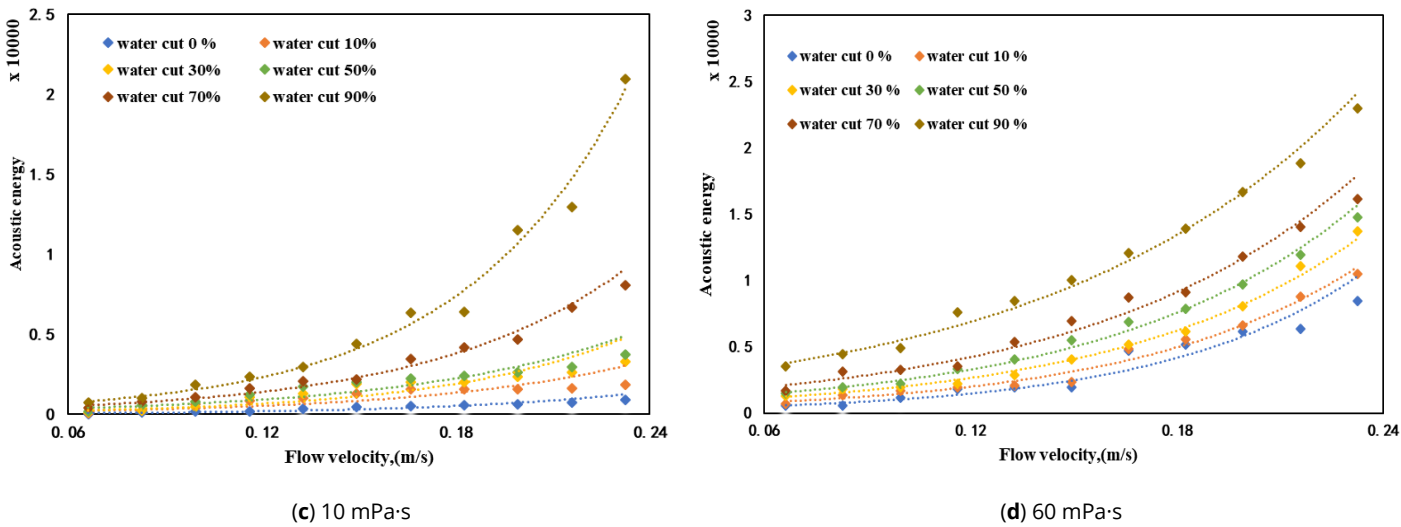


Figure 9: DAS acoustic energy versus average wellbore velocity at 0° inclination.

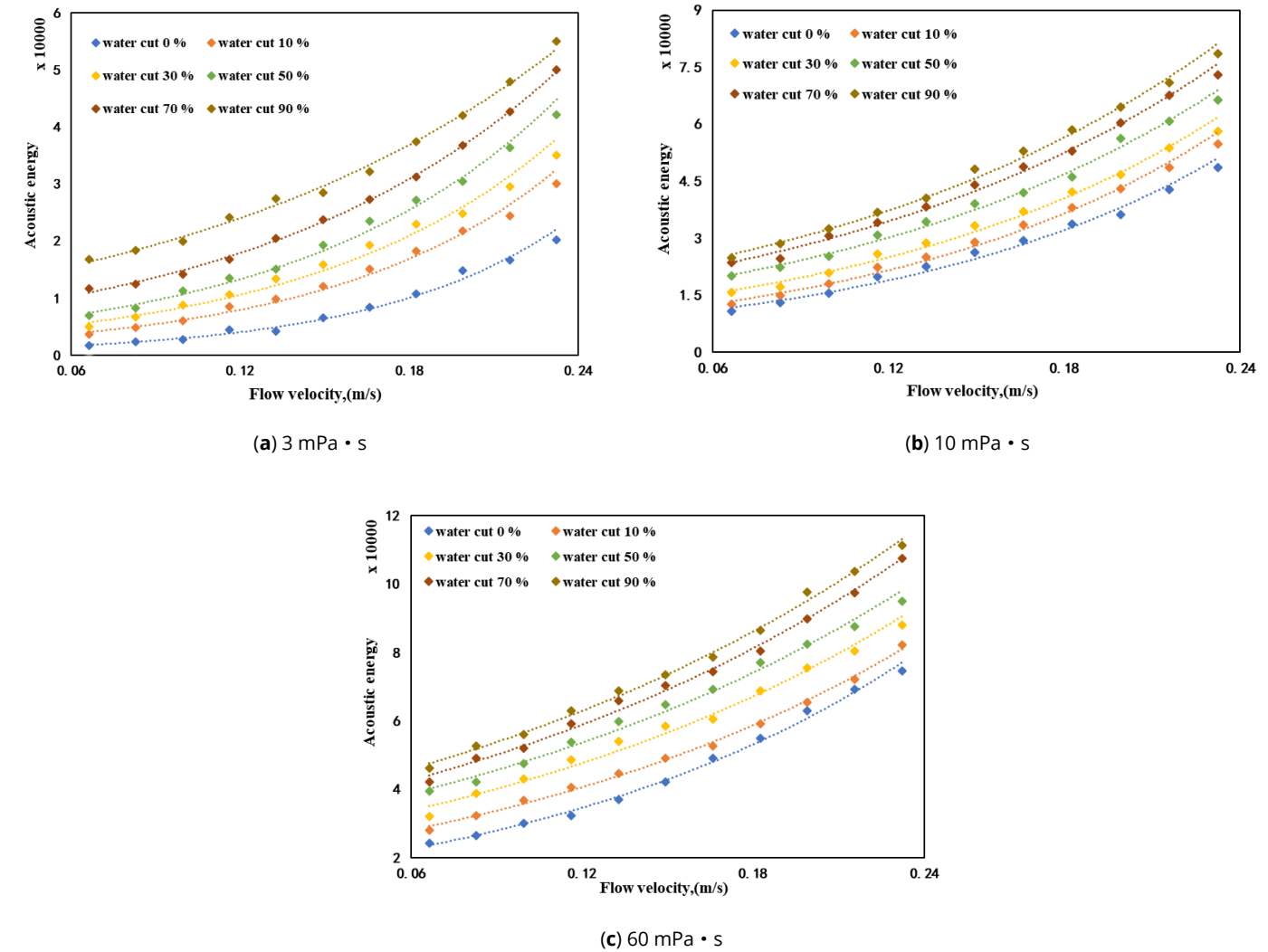


Figure 10: DAS acoustic energy versus average wellbore velocity at -15° inclination.

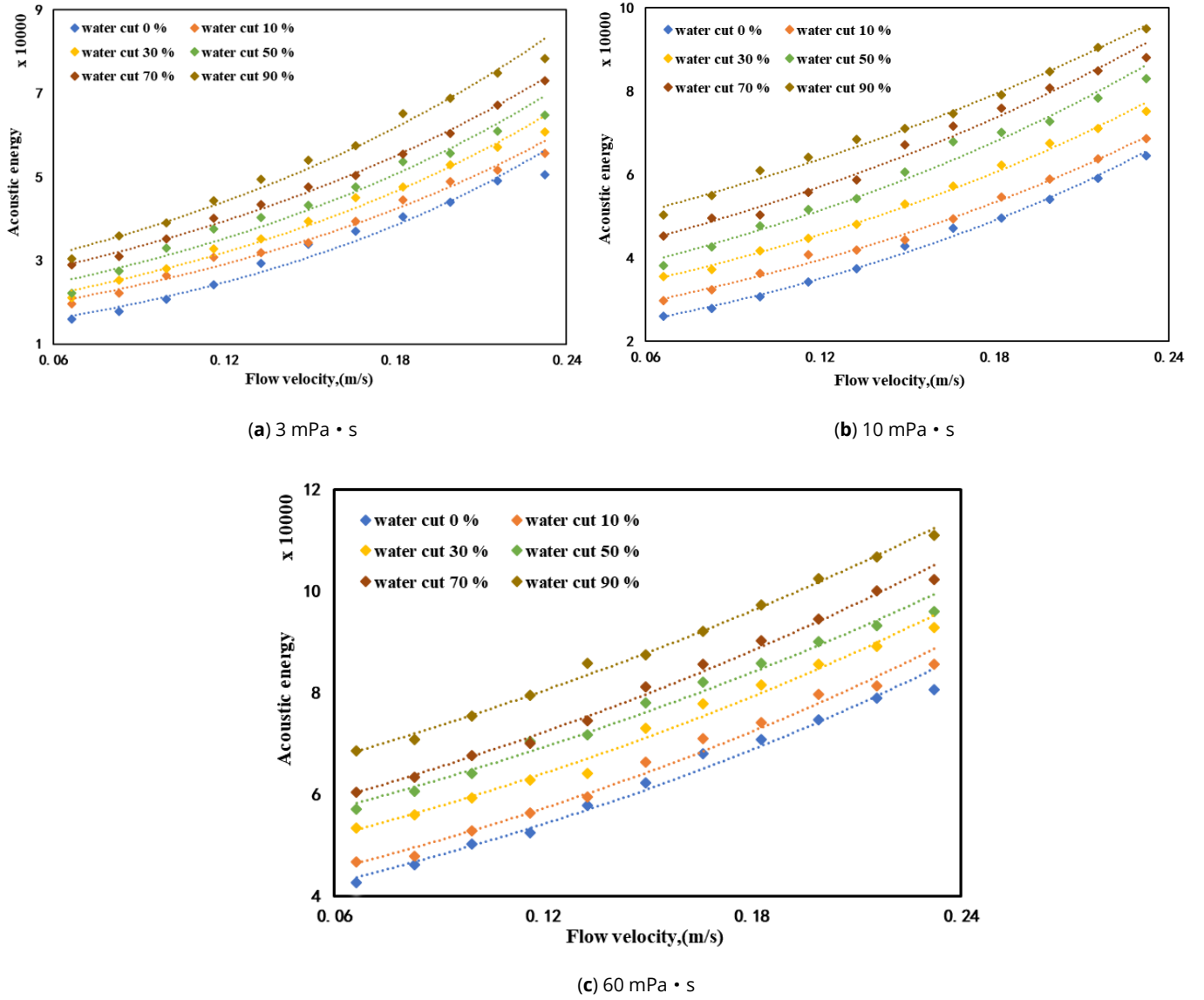


Figure 11: DAS acoustic energy versus average wellbore velocity at +15° inclination.

The experimental curves in Fig. (9–11) exhibit a monotonic nonlinear increase in DAS acoustic energy with average wellbore velocity. The approximately linear dependence of $\ln(E)$ on average wellbore velocity further supported the use of an exponential functional form. Based on this observed trend, an exponential model was fitted separately to each experimental condition by exponential regression. The coefficient of determination, R^2 , was used to evaluate the goodness of fit. For the subsequent uncertainty analysis, the exponential model was log-linearized as $\ln(E) = \ln(\alpha) + \beta v$, from which the standard errors of α and β and the 95% prediction intervals were estimated. The adopted exponential relationship is:

$$E = \alpha e^{\beta v} \quad (6)$$

where E is the DAS acoustic energy, v is the average wellbore velocity (m/s), and α and β are regression coefficients.

Because numerous fitted models are obtained for different combinations of crude-oil viscosity, water cut, and wellbore inclination, only representative conditions are presented in the main text to avoid excessive detail, as listed in Table 2.

Table 2: Fitted models and parameter uncertainty for average wellbore velocity versus DAS acoustic energy under representative conditions.

Incl. (°)	Visc. (mPa·s)	Water Cut (%)	Fitted Model	R ²	$\alpha \pm SE_{\alpha}$	$\beta \pm SE_{\beta}$
0°	-	100	$E=537.87e^{14.172v}$	0.9792	537.87 ± 58.66	14.172 ± 0.689
0°	3	0	$E=123.01e^{17.657v}$	0.8550	123.01 ± 37.96	17.657 ± 1.949
		10	$E=313.47e^{14.213v}$	0.9771	313.47 ± 34.65	14.213 ± 0.698
		30	$E=407.97e^{13.799v}$	0.9677	407.97 ± 51.47	13.799 ± 0.797
		50	$E=465.37e^{14.029v}$	0.9825	465.37 ± 42.03	14.029 ± 0.570
		70	$E=662.6e^{13.069v}$	0.9719	662.60 ± 107.63	13.069 ± 1.026
		90	$E=1311.1e^{10.437v}$	0.9881	1311.09 ± 103.43	10.437 ± 0.498
	10	30	$E=82.654e^{17.485v}$	0.8386	82.65 ± 33.12	17.485 ± 2.531
		90	$E=230.52e^{19.268v}$	0.9831	230.52 ± 26.82	19.268 ± 0.735
	60	30	$E=477.82e^{14.264v}$	0.9955	477.82 ± 35.75	14.264 ± 0.473
		90	$E=1797.5e^{11.178v}$	0.9913	1797.51 ± 125.19	11.178 ± 0.440
-15°	3	30	$E=2715.7e^{11.354v}$	0.9866	2715.65 ± 200.92	11.354 ± 0.467
		90	$E=10197e^{7.1453v}$	0.9954	10196.61 ± 285.83	7.145 ± 0.177
	10	30	$E=9486.3e^{8.069v}$	0.9906	9486.29 ± 407.76	8.069 ± 0.271
		90	$E=16226e^{6.9336v}$	0.9947	16225.86 ± 405.36	6.934 ± 0.158
	60	30	$E=23956e^{5.7272v}$	0.9892	23956.01 ± 909.61	5.727 ± 0.240
		90	$E=33598e^{5.2289v}$	0.9959	33597.91 ± 592.37	5.229 ± 0.111
+15°	3	30	$E=15054e^{6.2682v}$	0.9858	15054.44 ± 586.33	6.268 ± 0.246
		90	$E=22419e^{5.6359v}$	0.9853	22419.11 ± 785.30	5.636 ± 0.221
	10	30	$E=25875e^{4.7108v}$	0.9948	25874.53 ± 411.44	4.711 ± 0.100
		90	$E=41054e^{3.6499v}$	0.9925	41053.95 ± 815.13	3.650 ± 0.125
	60	30	$E=42036e^{3.5215v}$	0.9852	42036.20 ± 915.81	3.522 ± 0.138
		90	$E=56221e^{2.9802v}$	0.9953	56220.88 ± 620.31	2.980 ± 0.070

The exponential model and coefficient of determination R^2 for each condition were obtained by exponential regression of the experimental data. To quantify uncertainty in the regression parameters and model predictions, the exponential model was log-linearized, the standard errors (SEs) of α and β were calculated, and 95% prediction intervals were estimated from the regression residuals. Across the experimental conditions, the median relative half-width of the 95% prediction interval was 11.12%, with an interquartile range of 6.69%-24.36%. A small number of conditions exhibited wider prediction intervals because of greater scatter in the experimental data. For the pure-water condition, α and β were 537.87 ± 58.66 and 14.172 ± 0.689 , respectively, and the mean relative half-width of the 95% prediction interval was 29.90%. Overall, the exponential model described the relationship between DAS acoustic energy and average wellbore velocity with good stability for most experimental conditions, although prediction uncertainty varied among conditions.

4.3. Multifactor Coupled Response-Surface Model

The preceding analyses show that average wellbore velocity, crude-oil viscosity, water cut, and wellbore inclination all affect the DAS acoustic response. The exponential models above primarily describe the relationship between DAS acoustic energy and average wellbore velocity at fixed fluid properties and wellbore conditions. In

actual oil-water two-phase flow, however, these factors usually vary simultaneously, and a single-variable model cannot fully represent DAS responses under multifactor coupling.

Accordingly, on the basis of the exponential fits, response-surface methodology was used to develop a multifactor coupled model incorporating average wellbore velocity, crude-oil viscosity, water cut, and wellbore inclination. Because the variables have different dimensions and scales, the input parameters were first standardized as follows:

$$X_i = \frac{x_i - \bar{x}_i}{\sigma_i} \quad (7)$$

where X_i is the standardized variable, x_i is the original experimental variable, and $\bar{x}_i$ and σ_i are the corresponding mean and standard deviation, respectively.

The natural logarithm of DAS acoustic energy was used as the response variable:

$$Y = \ln(E) \quad (8)$$

A second-order response-surface model was then established:

$$Y = 7.9058 + 0.4877X_V + 0.2253X_A + 0.2698X_\mu + 0.3369X_{WC} - 0.0636X_V^2 + 1.8155X_A^2 + 0.1000X_\mu^2 - 0.0403X_{WC}^2 - 0.0741X_VX_A - 0.0558X_VX_\mu - 0.0472X_VX_{WC} - 0.1012X_AX_\mu - 0.0547X_AX_{WC} - 0.0544X_\muX_{WC} \quad (9)$$

where X_V 、 X_A 、 X_μ 、 X_{WC} denote the standardized average wellbore velocity, wellbore inclination, crude-oil viscosity, and water cut, respectively; the coefficients are the standardized regression coefficients of the response-surface model.

The model was fitted using the experimental data included in the response-surface analysis, yielding the coefficient of determination:

$$R^2 = 0.9159 \quad (10)$$

The adjusted coefficient of determination is:

$$R_{adj}^2 = 0.9139 \quad (11)$$

These values indicate that the model adequately describes the variation in DAS acoustic energy under simultaneous changes in multiple factors within the experimental range.

4.3.1. Analysis of Multifactor Coupling Effects

Analysis of the standardized regression coefficients shows that, among the four first-order terms, average wellbore velocity has the largest standardized coefficient and is the primary factor affecting DAS acoustic energy; water cut, crude-oil viscosity, and wellbore inclination also exert clear influences. DAS acoustic energy generally increases with average wellbore velocity. Changes in water cut and crude-oil viscosity also lead to differences in acoustic-energy response. The relatively large coefficient of the quadratic inclination term indicates a nonlinear influence of wellbore inclination on DAS response. The interaction terms show coupling between average wellbore velocity and both water cut and crude-oil viscosity, indicating that the sensitivity of DAS acoustic energy to average wellbore velocity varies with fluid properties.

4.3.2. Effects of Average Wellbore Velocity and Flow State

In the response-surface model, the first-order average-wellbore-velocity term has a greater influence than the quadratic velocity term. Within the experimental range, DAS acoustic energy therefore increases mainly with average wellbore velocity, while the nonlinear velocity contribution is relatively weak. Because the input variables were standardized, the magnitudes of the velocity coefficients can be compared directly within the response-surface model. The first-order velocity coefficient (0.4877) is substantially larger than the quadratic coefficient (-

0.0636), indicating that the dependence of $\ln(E)$ on average wellbore velocity is dominated by the first-order term, while the quadratic term contributes only weak additional curvature within the investigated range. It should be noted that X_p^2 is a standardized statistical basis term in the response-surface model and is not equivalent to the dimensional V^2 term in the Darcy-Weisbach pressure-drop relation. Therefore, the relatively small coefficient of X_p^2 does not by itself imply negligible kinetic energy or pressure drop; direct pressure-drop measurements would be required to support such a conclusion. Flow regimes were not directly observed in the present experiments; therefore, specific flow-regime transitions are not quantified. Future work may combine flow visualization, local phase-fraction measurements, and numerical simulation to further examine the relationships among average wellbore velocity, flow-regime evolution, and DAS response [44].

5. Conclusions

(1) Crude-oil viscosity, water cut, and wellbore inclination all affect DAS response characteristics. As crude-oil viscosity increases, the dominant DAS frequency shifts overall toward lower frequencies; DAS acoustic energy generally increases with water cut within the investigated oil-water two-phase conditions; and both spectral and energy responses differ clearly among inclinations, with acoustic energy following the overall order $+15^\circ > -15^\circ > 0^\circ$.

(2) DAS acoustic energy and average wellbore velocity exhibit an overall exponential relationship under different experimental conditions. The uncertainty analysis shows that the exponential model provides a stable description of the change in DAS acoustic energy with average wellbore velocity for most conditions, although prediction uncertainty varies among conditions. The model therefore provides a basis for subsequent DAS-based interpretation of wellbore flow parameters.

(3) A multifactor response-surface model incorporating average wellbore velocity, crude-oil viscosity, water cut, and wellbore inclination was established. Standardized regression results identify average wellbore velocity as the primary factor affecting DAS acoustic energy, while water cut, crude-oil viscosity, and wellbore inclination also have clear effects. Coupling was observed between average wellbore velocity and both water cut and crude-oil viscosity and the model can characterize DAS acoustic-energy responses when multiple factors vary simultaneously.

Conflict of Interest

The authors declare that they have no conflicts of interest that could have influenced the interpretation or publication of this study.

Funding

The study received no financial support.

References

- [1] Soroush M, Mohammadtabar M, Roostaei M, Hosseini SA, Fattahpour V, Mahmoudi M, *et al.* Downhole monitoring using distributed acoustic sensing: fundamentals and two decades deployment in oil and gas industries. SPE Conference at Oman Petroleum & Energy Show; 2022. SPE-200088-MS. <http://doi.org/10.2118/200088-MS>
- [2] Li X, Liu X, Zhang Y, Guo F, Wang X, Feng Y. Application and progress of oil and gas well monitoring techniques based on distributed optical fiber sensing. Oil Drill Prod Technol. 2022; 44(3): 309-20. <http://doi.org/10.13639/j.odpt.2022.03.007>
- [3] Masoudi A, Belal M, Newson TP. A distributed optical fibre dynamic strain sensor based on phase-OTDR. Meas Sci Technol. 2013; 24(8): 085204. <http://doi.org/10.1088/0957-0233/24/8/085204>
- [4] Johannessen K, Drakeley BK, Farhadiroushan M. Distributed acoustic sensing—a new way of listening to your well/reservoir. Paper presented at: SPE Intelligent Energy International; 2012; Utrecht, The Netherlands. SPE-149602-MS. <http://doi.org/10.2118/149602-MS>
- [5] Daley TM, Freifeld BM, Ajo-Franklin J, Dou S, Pevzner R, Shulakova V, *et al.* Field testing of fiber-optic distributed acoustic sensing (DAS) for subsurface seismic monitoring. Leading Edge. 2013; 32(6): 699-706. <http://doi.org/10.1190/tle32060699.1>

- [6] Xing X, Chen H, Yu J, Fan B, Wu Z. Gas-liquid two-phase flow in large liquid horizontal gas wells with different gas lift modes. *Sci Technol Eng.* 2022; 22(28): 12362-9.
- [7] Liu DW, Yang BJ, Zhang WB, *et al.* Analysis of Gas-Liquid Two-Phase Flow Characteristics in Horizontal Wellbores. *China Petroleum and Chemical Standard and Quality.* 2023; 43(15): 81–84.
- [8] He H. Application of distributed fiber optic DAS logging technology in fracturing monitoring of offset wells in shale gas horizontal wells. *J Jiangnan Pet Univ Staff Workers.* 2025; 38(1): 15-8.
- [9] He L, Zhu J, Liang X, Zhao Z, Guan B, An S. Evaluation of multi-cluster fracturing effects in horizontal shale gas wells based on optic fiber monitoring outside casing. *Pet Drill Tech.* 2024; 52(4): 110-7.
- [10] Liu J, Han Y, Jia Q, Zhang L, Liu M, Li Z. Oil-water flowing experiments and water-cut range classification approach using distributed acoustic sensing. *SPE J.* 2024; 29(3): 1238-53. <http://doi.org/10.2118/218389-PA>
- [11] Angeli P, Hewitt GF. Flow structure in horizontal oil-water flow. *Int J Multiphase Flow.* 2000; 26(7): 1117-40. [http://doi.org/10.1016/S0301-9322\(99\)00081-6](http://doi.org/10.1016/S0301-9322(99)00081-6)
- [12] Trallero JL, Sarica C, Brill JP. A study of oil-water flow patterns in horizontal pipes. *SPE Prod Facil.* 1997; 12(3): 165-72. <http://doi.org/10.2118/36609-PA>
- [13] Zharnikov T, Alekseev D, Aloqili SA, Zelenyy M, Jacob S, Tammar A. Downhole leak detection using high frequency DAS and DTS signals from fiber optics cables. Paper presented at: Middle East Oil, Gas and Geosciences Show (MEOS GEO); 2025; Manama. SPE-227100-MS. <http://doi.org/10.2118/227100-MS>
- [14] Deng R, Gan L, Shi Y, Zhang H, Bai S, Duan C, *et al.* Data processing method of DAS logging. Paper presented at: SPWLA 66th Annual Logging Symposium; 2025; Dubai, UAE. SPWLA-2025-0064. <http://doi.org/10.30632/SPWLA-2025-0064>
- [15] Fidaner O. Downhole multiphase flow monitoring using fiber optics. Paper presented at: SPE Annual Technical Conference and Exhibition; 2017; San Antonio, TX, USA. SPE-187415-MS. <http://doi.org/10.2118/187415-MS>
- [16] Hu X, Jiang Z, Wang X, Zhou F, Zhao Y, Gong H, *et al.* Calculation of fluid-producing profiles from mine fiber-optic acoustic data: model and application. *Pet Sci Bull.* 2025; 10(3): 553-64. <http://doi.org/10.3969/j.issn.2096-1693.2025.02.006>
- [17] Luo H, Chen B, Li H. Production profile inversion method of horizontal well in oil reservoir based on DAS. *Chin J Sens Actuators.* 2025; 38(12): 2192-9.
- [18] Xiao JJ, Farhadiroushan M, Clarke A, Abdalmohsen RA, Alyan E, Parker TR, *et al.* Intelligent distributed acoustic sensing for in-well monitoring. Paper presented at: SPE Saudi Arabia Section Technical Symposium and Exhibition; 2014; Al-Khobar, Saudi Arabia. SPE-172197-MS. <http://doi.org/10.2118/172197-MS>
- [19] Shirdel M, Buell RS, Wells MJ, Muharam C, Sims JC. Horizontal-steam-injection-flow profiling using fiber optics. *SPE J.* 2019; 24(2): 431-51. <http://doi.org/10.2118/181431-PA>
- [20] Chavarria JA, Grubert M, Minto C, Adams E. Well integrity surveillance with high sensitivity temperature distributed sensing. Paper presented at: ADIPEC; 2022; Abu Dhabi, UAE. SPE-211270-MS. <http://doi.org/10.2118/211270-MS>
- [21] Hashish RG, Spivey BJ, Walker K, Campbell B, Seabrook B. Machine learning for flow rate and AICD status prediction using distributed acoustic sensing data. Paper presented at: SPE Annual Technical Conference and Exhibition; 2025; Houston, TX, USA. SPE-228077-MS. <http://doi.org/10.2118/228077-MS>
- [22] Li BB, Liu WQ, Huo Y, Li D, Zhang JL, Ren JW, *et al.* Research on a distributed optical fiber massive DAS data preprocessing and noise reduction filtering method. In: Lin J, Ed. *Proceedings of the International Field Exploration and Development Conference 2024.* Singapore: Springer; 2025. p. 659-77. http://doi.org/10.1007/978-981-96-2896-4_46
- [23] Mallat S. *A wavelet tour of signal processing: the sparse way.* 3rd ed. Burlington: Academic Press; 2009. p. 83-5.
- [24] Daubechies I. The wavelet transform, time-frequency localization and signal analysis. *IEEE Trans Inf Theory.* 1990; 36(5): 961-1005. <http://doi.org/10.1109/18.57199>
- [25] Huang NE, Shen Z, Long SR, Wu MC, Shih HH, Zheng Q, *et al.* The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. *Proc R Soc A.* 1998; 454(1971): 903-95. <http://doi.org/10.1098/rspa.1998.0193>
- [26] Wilson RE, Eckley IA, Nunes MA, Park T. Dynamic detection of anomalous regions within distributed acoustic sensing data streams using locally stationary wavelet time series. *Data Min Knowl Disc.* 2019; 33(3): 748-72. <http://doi.org/10.1007/s10618-018-00608-w>
- [27] Ajo-Franklin JB, Dou S, Lindsey NJ, Monga I, Tracy C, Robertson M, *et al.* Distributed acoustic sensing using dark fiber for near-surface characterization and broadband seismic event detection. *Sci Rep.* 2019; 9: 1328. <http://doi.org/10.1038/s41598-018-36675-8>
- [28] Jousset P, Reinsch T, Ryberg T, Blanck H, Clarke A, Aghayev R, *et al.* Dynamic strain determination using fibre-optic cables allows imaging of seismological and structural features. *Nat Commun.* 2018; 9: 2509. <http://doi.org/10.1038/s41467-018-04860-y>
- [29] Dong L, Zhang M, Zhang W. Design and simulation of Butterworth low-pass digital filter based on MATLAB. *Sci Technol Vis.* 2016; (21): 96-7.
- [30] Xu PJ. Study on fluid flow characteristics in inclined wellbore based on DAS monitoring and Fluent simulation (dissertation). Yangtze University; 2025.
- [31] Tan G, Liu F, Huang X, Zhou T, Zeng H, Zhu G, *et al.* Noise reduction of distributed acoustic sensor for downhole flow monitoring. In: 28th International Conference on Optical Fiber Sensors; 2023 Nov 20-24; Naka-ku, Hamamatsu-shi, Japan. Optica Publishing Group; 2023. p. Tu3.47. <http://doi.org/10.1364/OFS.2023.Tu3.47>

- [32] Lindsey NJ, Martin ER, Dreger DS, Freifeld B, Cole S, James SR, *et al.* Fiber-optic network observations of earthquake wavefields. *Geophys Res Lett.* 2017; 44(23): 11792-9. <http://doi.org/10.1002/2017GL075722>
- [33] Butterworth S. On the theory of filter amplifiers. *Exp Wireless Wirel Eng.* 1930; 7: 536-41.
- [34] Luo H, Li H, Li H, Zhang X. Experimental study on DAS response characteristics of oil-water two-phase inflow in horizontal wells. *Well Logging Technol.* 2025; 49(6): 970-8.
- [35] Nädler M, Mewes D. Flow induced emulsification in the flow of two immiscible liquids in horizontal pipes. *Int J Multiphase Flow.* 1997; 23(1): 55-68. [http://doi.org/10.1016/S0301-9322\(96\)00055-9](http://doi.org/10.1016/S0301-9322(96)00055-9)
- [36] Brauner N. The prediction of dispersed flows boundaries in liquid-liquid and gas-liquid systems. *Int J Multiphase Flow.* 2001; 27(5): 885-910. [http://doi.org/10.1016/S0301-9322\(00\)00056-2](http://doi.org/10.1016/S0301-9322(00)00056-2)
- [37] Beggs DH, Brill JP. A study of two-phase flow in inclined pipes. *J Pet Technol.* 1973; 25(5): 607-17. <http://doi.org/10.2118/4007-PA>
- [38] Mukherjee H, Brill JP. Pressure drop correlations for inclined two-phase flow. *J Energy Resour Technol.* 1985; 107(4): 549-54. <http://doi.org/10.1115/1.3231233>
- [39] Bukhamsin A, Horne R. Cointerpretation of distributed acoustic and temperature sensing for improved smart well inflow profiling. Paper presented at: SPE Western Regional Meeting; 2016 May; Anchorage, AK, USA. SPE-180465-MS. <http://doi.org/10.2118/180465-MS>
- [40] Hartog AH. An introduction to distributed optical fibre sensors. Boca Raton: CRC Press; 2017. <http://doi.org/10.1201/9781315119014>
- [41] Ünalmsis ÖH. Downhole three-phase flow measurement using sound speed measured by local or distributed acoustic sensing. Paper presented at: SPE Annual Technical Conference and Exhibition; 2022 Oct; Houston, TX, USA. SPE-210072-MS. <http://doi.org/10.2118/210072-MS>
- [42] Ünalmsis ÖH. A methodology for in-well multiphase flow measurement with strategically positioned local and/or distributed acoustic sensors. *Sensors (Basel).* 2023; 23(13): 5969. <http://doi.org/10.3390/s23135969>
- [43] Hveding F, Bukhamsin A. Distributed fiber optic sensing: a technology review for upstream oil and gas applications. Paper presented at: SPE Kingdom of Saudi Arabia Annual Technical Symposium and Exhibition; 2018 Apr; Dammam, Saudi Arabia. SPE-192323-MS. <http://doi.org/10.2118/192323-MS>
- [44] Shoham O. Mechanistic modeling of gas-liquid two-phase flow in pipes. Richardson, TX: Society of Petroleum Engineers; 2006. <http://doi.org/10.2118/9781555631079>