# Noise analysis and ML denoising of DAS VSP data acquired from ESP lifted wells

*Ge Zhan*, Yao Zhao, Cheng Cheng, and Josef Heim, TGS; Weihong Fei, Mike Craven, Scott Baker, and Gilles Hennenfent, Chevron*

## Summary

3D DAS VSP data were acquired in two active wells equipped with Electrical Submersible Pumps (ESPs) from the Big Foot field in the deep water, Gulf of Mexico. During the VSP survey, the wells remained producing most of the time with downhole ESPs operating at normal frequencies. Both seismic signals and ESP related noise were recorded by fiber optic cables installed inside the wellbore. In this paper, we compare DAS VSP data recorded with and without the ESP running and perform an analysis of the characteristics of flow noise activated by the ESP. We also use a machine learning (ML) algorithm based on supervised deep learning for attenuating ESP noise and present promising results.

## Introduction

Distributed acoustic sensing (DAS) as an emerging technology for acquiring vertical seismic profiling (VSP) data (Mestayer et al., 2011) has earned a lot of attention in industry. In recent years, low-cost 3D/4D DAS VSP acquisitions using fiber optic cables as sensors are widely taking the place of high-cost conventional geophone VSP surveys, as they provide most of the value of a geophone VSP acquisition for 3D imaging and 4D monitoring in the vicinity of the well (Zhan et al., 2015; Mateeva et al., 2017). Most importantly, DAS VSP surveys can be conducted in active wells without any well intervention or production interruption, which further improves the cost effectiveness and acquisition flexibility.

Over the last five years, numerous 3D and 4D DAS VSP datasets were collected in active producer or injector wells in several fields by different operators. The noise levels of these data are higher compared to DAS data acquired in a shut-in well due to noise from in-well fluid flow. Although the unwanted flow noise recorded by DAS VSP degrades the quality of the desired seismic signal, it has been shown that after adequate processing, 3D and 4D DAS can provide useful images from fiber optic cables recording in flowing wells (Kiyashchenko et al., 2019; Zhan and Nahm, 2020).

Our literature investigation showed previous DAS VSP data were acquired either on quiet wells or natural-flowing wells. This paper describes DAS VSP field data acquired on one of two Electrical Submersible Pump (ESP) lifted wells from the Big Foot field in Gulf of Mexico. To our knowledge, this was the first DAS VSP acquisition in wells with the ESP running. This paper also presents how the ESP-related flow noise were analyzed for understanding the noise characteristics, followed by noise removal using ML.

## Pre-survey Recording and Signal/Noise Analysis

To ensure the quality of the downhole fiber optic cable for seismic recording, as well as to understand the production noise level, we acquired a few hours' passive DAS data on the same production well in August 2021 prior to the seismic survey. The continuous data contains both background noise and flow noise without seismic. Figure 1 shows the DAS recording as passive monitoring of a production well and compares three representative flow states observed over the recording period.

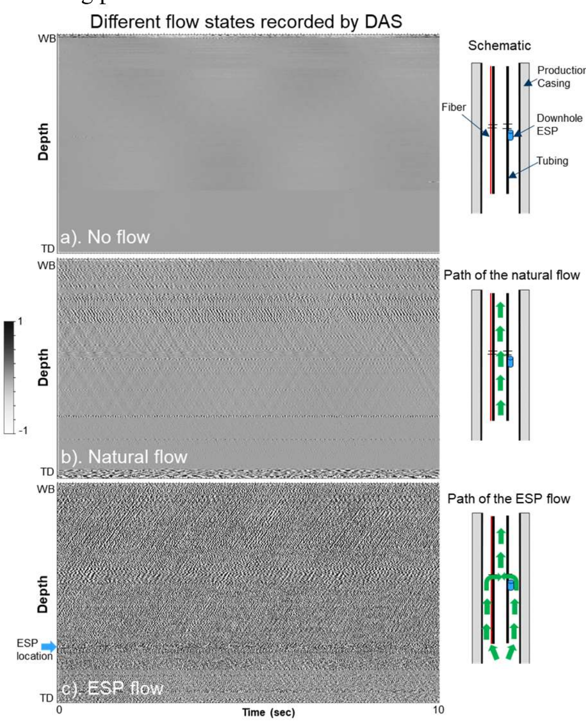


Figure 1: DAS passive recording (10 s) of a production well. a) was recorded during quiet time when there was no flow in the well; b) and c) were recorded during flow time without and with the ESP running, respectively. The column on the right depicts well schematic and corresponding flow paths when the ESP is off or on.

The fiber optic cable was strapped to the outside of the tubing with clamps, as shown in Figure 1. With no flow in the well (Figure 1a), the downhole fiber seems sensitive enough to detect weak ambient signals at a frequency as low as 0.2 Hz. They look like ocean noise that is commonly observed. Production noise (Figure 1b) due to natural flow in the wellbore demonstrates itself on a DAS record as repetitive low-frequency tube waves, which show both


10.1190/image2022-3750545.1

upgoing and downgoing travel along the tubing. After the ESP was turned on, the downhole pressure was boosted and fluid below the ESP depth flowed in the annulus outside of the tubing. Strong high-frequency noise is seen at the ESP location on the DAS record shown in Figure 1c due to a pump running at ~44 Hz. Tube wave energy which correlates with the pump speed had also been boosted by approximately an order of magnitude.

Time-frequency spectra of DAS noise data within a 60 s time window are shown in Figure 2. The background noise (Figure 2a) exhibits as low-frequency components (< 2 Hz), while the natural flow (Figure 2b) results in several mono frequency bands along the time axis with two pronounced peaks between 10 Hz and 20 Hz. The ESP flow noise also demonstrates morphological characteristics with the highest peak at the ESP running frequency ($f_{ESP}$ = 44 Hz in this case) and two other peaks at the corresponding harmonic frequency ($2 * f_{ESP}$) and subharmonic frequency ($f_{ESP}/2$).

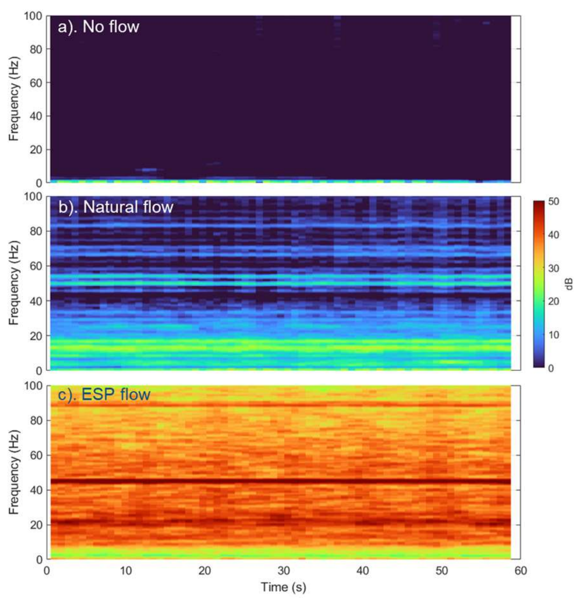


Figure 2: Spectrograms of DAS continuous data with no flow (a), natural flow (b), and ESP flow (c).

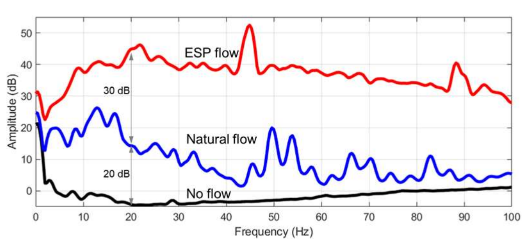


Figure 3: Comparison of natural flow noise and ESP flow noise relative to background noise with no flow.

Figure 3 compares amplitude spectra between background noise and flow noise resulting from natural flow and ESP flow. At 20 Hz, the noise level of natural flow is ~20 dB above the background noise floor and it was further boosted by another 30 dB when the ESP was in operation.

### 3D DAS VSP Acquisition and Field Data

In October 2021, 3D DAS VSP data of two wells were acquired simultaneously using a 5040 cubic inch source vessel in the Big Foot field located in the deep water, Gulf of Mexico. The acquisition geometry is provided below in Figure 4a. Over 60,000 airgun shots were fired in a 19.5 km x 7.5 km N-S grid over the borehole region. With more than 7,000 channels at every 1.02 m spatial sampling on each fiber with a gauge length of 10 m, a total of 75 TB DAS continuous data were recorded in two wells over a period of 3.5 weeks.

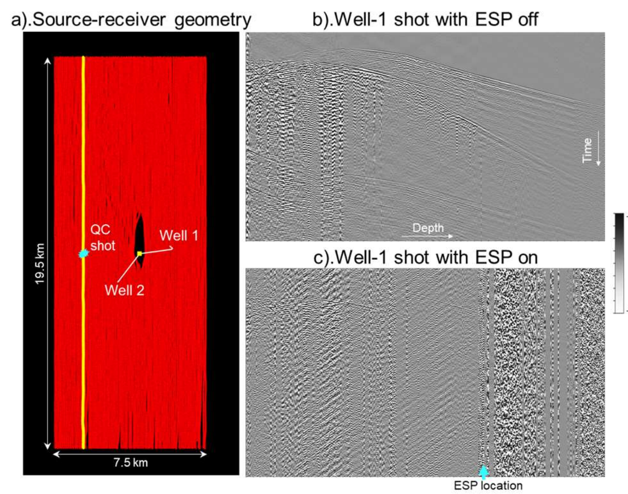


Figure 4: a). Dual-well DAS VSP acquisition geometry. The shots are drawn as red lines and the two white line segments around the platform are fibers in two wells. b) and c) are two co-located shots from the middle of the yellow line which were acquired at separate times of the survey when the ESP was off and on.

When the well is quiet with no flow, the Well-1 DAS data (Figure 4b) is of sufficient quality that first breaks, multiple arrivals, and converted waves are clearly seen on a raw shot located 2.5 km away from the wellhead. However, after the downhole ESP was turned on, the DAS data (Figure 4c) from the same well and same shot location was completely overridden by the strong noise generated by the ESP pump. The first arrivals become difficult to track as channels above the ESP were contaminated by ESP-induced tube waves traveling from the downhole ESP location upward to the seafloor. Channels below the ESP were severely affected by high energy flow noise due to direct interaction between the fiber and well fluid.



10.1190/image2022-3750545.1

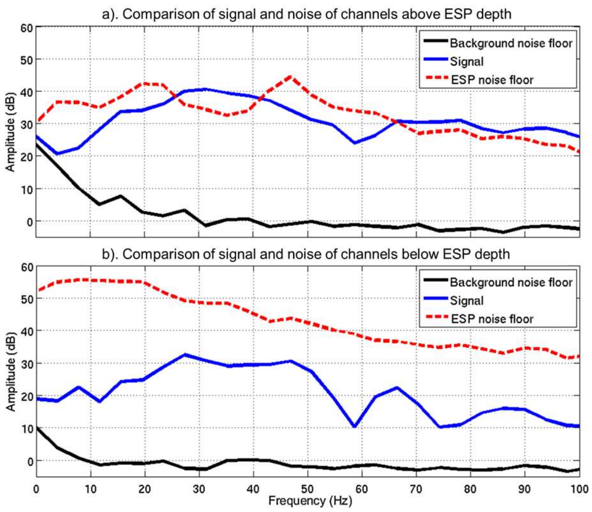


Figure 5: Signal and noise amplitude spectra of DAS channels above (a) and below (b) the ESP depth. The data windows for the signal calculations were chosen to only include VSP downgoing first arrivals. For the noise calculations, data in a window above the first arrivals were used.

The frequency responses of noise (above the first arrivals) and seismic signals (downgoing first arrivals) are shown in Figure 5. When the ESP was off, the signal-to-noise-ratio (SNR) is up to 40 dB for channels above the ESP and 30 dB for channels below the ESP. In the case of the ESP running, flow noise demonstrates the broadband noise characteristics with a similar (above the ESP) or higher (below the ESP) level of amplitude compared to seismic signals.

## ESP noise attenuation via machine learning

Traditional denoising is always difficult under extreme low SNR conditions, especially when the noise frequency overlaps with the signal's frequency. To address the challenge of ESP noise attenuation presented in the Big Foot DAS data, we developed a machine learning (ML) workflow that uses a deep convolutional U-Net architecture to model the ESP noise first and then subtract it from the raw DAS data. The network consists of an encoder-decoder framework with symmetric convolutional-deconvolutional layers and skip connections (Figure 6). Details can be found in the paper by Valenciano et al. (2022).

A pair of DAS input gathers (noise gathers and noise-free gathers) and the desired output (noise model) are provided in a typical supervised model training. Although it is easy to obtain input noise gathers (i.e., pure ESP noise) for ML, finding the associated noise-free gathers is often not trivial. Fortunately, we have acquired a few sail lines (5 out of 76) that are free of ESP noise when the pump was off during downtime of the well. A combination of noise-free gathers and pure ESP noise recorded from the field is used as an input to our ML model. Then we train the network to obtain an accurate ESP noise prediction model from this input data.

According to the noise analysis, we found that the ESP noise level is a function of both pump speed and fiber channel depth. Since the pump speed didn't change much in time, the level of the ESP noise mainly varies with channel depth. Therefore, we decided to work with data patches randomly extracted from common channel gathers instead of common shot gathers in the training dataset. Augmentation techniques such as scaling, changing polarity, and horizontal flipping have been applied to further enhance the dataset statistics. We have trained our model based on 5 ESP noise-free lines and then applied it to all 76 shot lines.

The results of the ML denoise are shown in Figure 7. A group of input DAS channel gathers are shown in Figure 7a. The noise pattern and amplitude vary considerably with channel depth mainly due to different coupling conditions between fiber and tubing along the wellbore. Figure 7b displays ESP noise modeled by ML, and denoised gathers with ESP noise effectively removed are shown in Figure 7c. The ML denoised gathers were also compared to field data recorded at the same channel/shot location but at a different time when the ESP was off (Figure 7d). The close similarity between the ML denoised data and the noise-free field data further demonstrates the performance and effectiveness of the presented ML denoising workflow.

## Conclusions

Field DAS VSP data acquired from ESP lifted wells were presented. Noise analysis of passive DAS data with no flow, natural flow and ESP flow was carried out. The natural flow noise is 20 dB above the background noise level while the ESP flow noise is 30 dB louder than the natural flow noise. The comparison of DAS VSP data recorded in the same well with and without the ESP running showed that the overwhelming ESP noise significantly distorted seismic signals in terms of amplitude and frequency and made the subsequent seismic signal processing difficult. To tackle the ESP noise, a deep convolutional U-net architecture was adapted and a ML denoising workflow was developed. It resulted in encouraging denoised data which are comparable to field DAS data recorded without the ESP noise.

## Acknowledgements

The authors would like to thank Chevron, Equinor and Marubeni for permission to publish the DAS field data and results. We also thank TGS for permission to publish this paper. We especially thank Scott Michell, Bin Wang, Sarah Spoors, Faqi Liu, Zhaojun Liu, Alejandro Valenciano and other colleagues at TGS for fruitful discussions.

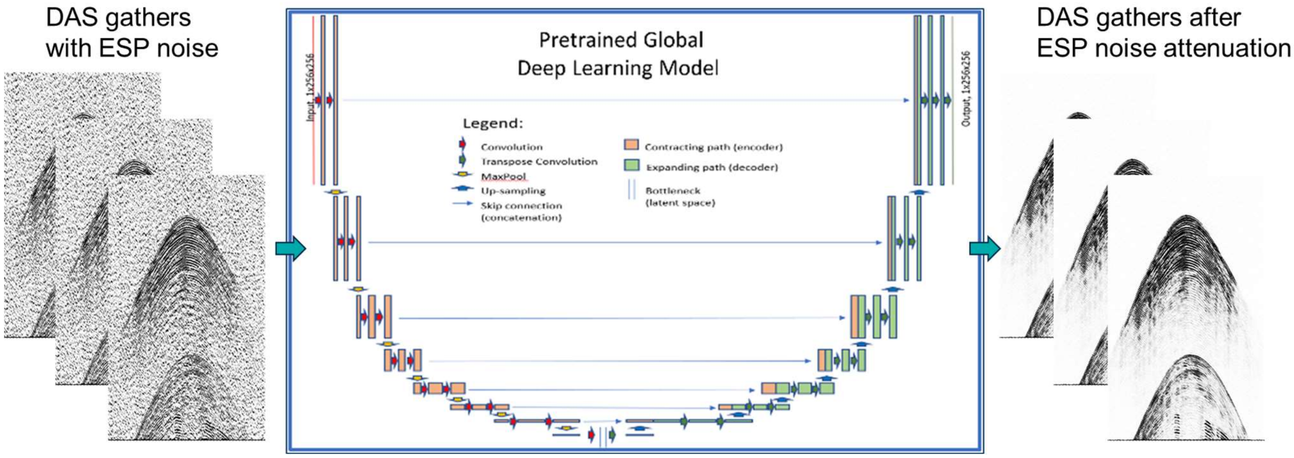


Figure 6: Deep-learning ESP noise attenuation workflow.

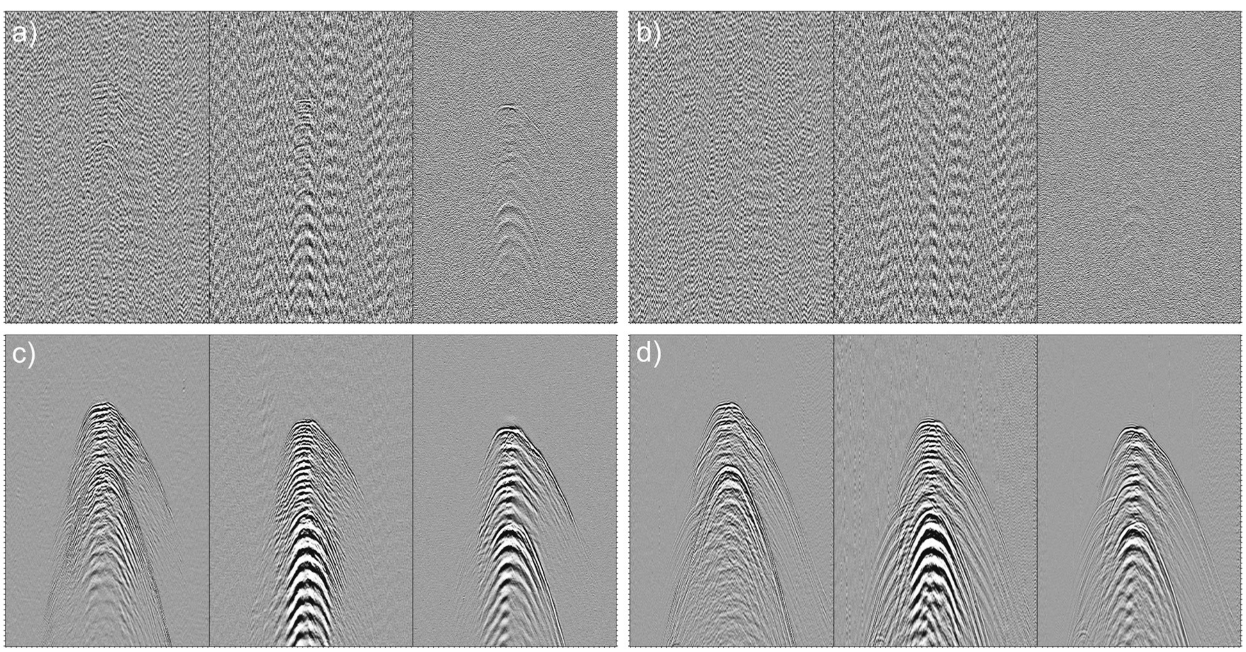


Figure 7: Deep-learning ESP noise attenuation results. a) ML input: raw DAS channel gathers from shallow to deep which were all containminated by strong ESP noise. b) ML output: ESP noise model predicted from supervised deep learning. c) Denoised DAS channel gathers after ML noise prediction and subtraction. d) Field recorded ESP noise-free gathers of the same channels and shot locations acquired at a different time window when the ESP was off.



10.1190/image2022-3750545.1

## REFERENCES


Kiyashchenko, D., Y. Duan, A. Mateeva, D. Johnson, J. Pugh, A. Geisslinger, and J. Lopez, 2019, Maturing 4D DAS VSP for on-demand seismic monitoring in deepwater: 89th Annual International Meeting, SEG, Expanded Abstracts, 5285–5289, doi: https://doi.org/10.1190/segam2019-3216625.1.

Mateeva, A., J. Lopez, D. Chalenski, M. Tatanova, P. Zwartjes, Z. Yang, S. Bakku, K. de Vos, and H. Potters, 2017, 4D DAS VSP as a tool for frequent seismic monitoring in deep water: The Leading Edge, **36**, 995–1000, doi: https://doi.org/10.1190/tle36120995.1.

Mestayer, J., B. Cox, P. Wills, D. Kiyashchenko, J. Lopez, M. Costello, S. Bourne, G. Ugueto, R. Lupton, G. Solano, D. Hill, and A. Lewis, 2011, Field trials of distributed acoustic sensing for geophysical monitoring: 81st Annual International Meeting, SEG, Expanded Abstracts, 4253–4257, doi: https://doi.org/10.1190/1.3628095.

Valenciano, A., O. Brusova, and C. Cheng, 2022, Efficient swell noise removal using a global deep neural network model: First Break, **40**, 51–55, doi: https://doi.org/10.3997/1365-2397.fb2022012.

Zhan, G., and J. Nahm, 2020, Multi-well 3D DAS VSPs: Illumination and imaging beyond the wellbores: 90th Annual International Meeting, SEG, Expanded Abstracts, 3798–3802, doi: https://doi.org/10.1190/segam2020-3426032.1.

Zhan, G., J. Kommedal, and J. Nahm, 2015, VSP field trials of distributed acoustic sensing in Trinidad and Gulf of Mexico: 85th Annual International Meeting, SEG, Expanded Abstracts, 5539–5543, doi: https://doi.org/10.1190/segam2015-5876420.1.