Microseismic Monitoring and Analysis with Cutting-Edge Technology

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Microseismic monitoring is a useful enabler for reservoir characterization without which the information on the effects of reservoir operations such as hydraulic fracturing, enhanced oil recovery, carbon dioxide, or natural gas geological storage would be obscured. The global energy demand is projected to increase. To meet the increasing energy demand requires new technologies to exploit unconventional reserves. Similarly, calls for climate actions such as carbon geosequestration, hydrogen generation, and geological hydrogen storage will require an improvement in reservoir characterization methods.

microseismic monitoring deep learning distributed acoustic sensors

1. Introduction

The global energy demand is projected to increase. To meet the increasing energy demand requires new technologies to exploit unconventional reserves. Similarly, calls for climate actions such as carbon geosequestration, hydrogen generation, and geological hydrogen storage will require an improvement in reservoir characterization methods [1][2][3][4]. Seismology remains one of the most relevant instruments in reservoir characterization. The importance of seismology in reservoir characterization is extensively covered in the literature [5][6][7][8][9].

2. Microseismology in Reservoir Characterization

Estimating the petrophysical properties of reservoirs is integral to reserve and resource estimation. While petrophysical measurements from well logs adequately evaluate the reservoir properties, the correlation with seismic data better validates the measured properties and reduces errors [10][11]. The availability of continuous microseismic data helps people to understand the geomechanical and petrophysical changes in the reservoir. Furthermore, the real-time data and analysis of such petrophysical changes could contribute to the initial screening process of feasible enhanced oil recovery methods [12].

Hydraulic fracturing is one of the most popular techniques for enhanced oil recovery and geothermal production. It involves the injection of huge volumes of a special liquid under high pressure into the geological formations to create new fractures and open up existing ones. Since this process has a direct mechanical effect on the geological formations, there is a potential to induce microseismic events locally. Foulger [13] indicated that about 21 earthquakes were induced due to hydraulic fracturing. Similar geological exploitation such as geothermal energy extraction has also been reported to have an increased microseismic rate [14][15].

Numerous processes involving the injection of gases have been at the forefront of studies in recent years. While the techniques of injecting CO_2 into geological formations are well advanced, the assurance of the safety of the storage sites for many years to come remains an unanswered question. The storage of CO_2 presents potential changes in the physical, chemical, and mechanical state of the geological formations and in situ reservoir brine [16][17][18][19][20]. An example was demonstrated in the study by Oye et al. [21], who showed the occurrence of microseismic events in clusters within a limited spatial area, which was attributed to CO_2 injection. Hydrogen gas requires higher storage volumes due to its low volume to burn ratio [22]. One of the proposed storage solutions for hydrogen for future use is its storage in geological formations [23][24]. The concern of this storage mechanism is the possible induction of microseismic events due to pressure build-up as well as the loss of hydrogen in the geological formation [25]. Similar concerns have been attributed to the underground storage of gas [26].

At the end of the life cycle of a well, a well abandonment and decommissioning operation is implemented to isolate and prevent the further inflow of hydrocarbons or the migration of hydrocarbons upward, which could contaminate the upper layer water-bearing zones. However, while the techniques implored in well plugging and abandonment are well advanced, the longevity of the integrity of the well is difficult to predict. Hence in most cases, there is a need for the continuous monitoring of wellbore integrity and other previously induced microseismic events [27][28].

3. DAS in Reservoir Characterization

For a long time, three-dimensional vertical seismic profiling (3D-VSP) has been considered as appealing for imaging complex subsurface structures, both in exploration and time-lapse monitoring for the characterization of reservoirs. However, the associated costs and complexity of installing geophone arrays in a well as well as the scarcity of available wells have hampered the widespread deployment of 3D-VSP [29]. These challenges can essentially be reduced by the use of the novel distributed acoustic sensing (DAS) technology.

DAS uses an ordinary or engineered fiber optic cable for seismic monitoring. In its deployment, an interrogation unit (IU) is attached at the end of the fiber optic cable near or on the surface. The IU measures the deformations (contractions or extensions) along the fiber optic cable caused by propagating seismic waves. This sort of measurement is known as distributed acoustic sensing. “Distributed” because any part of the fiber cable can be deformed and logged for seismic information.

DAS measurements are straightforward in concept. A laser pulse is sent down the fiber cable by the IU. As the pulse propagates through the cable, portions of it undergo Rayleigh back-scattering due to the minute heterogeneities in the cable. When a seismic wave interacts with the cable, deforming it, it causes changes in the patterns of the back-scattered light, which is then converted into seismic data. The time it takes the back-scattered pulse to travel back to the IU allows for an accurate location of the point of deformation. Due to the fast speed of light, the entire length of the fiber optic cable can be interrogated with laser pulses at frequencies far greater than those of seismic waves. Depending on the length of the borehole, the interrogation frequencies typically range from 10 to 100 kHz, with higher frequencies known to produce a higher signal-to-noise ratio (SNR) due to redundancy. Nonetheless, the length of the borehole restricts the highest permissible frequency.

The first demonstration of the capability of use of DAS for VSP acquisition was by Mestayer et al. [30]. There has since been tremendous progress in the development and testing of DAS technology that has resulted in its almost unrivalled acceptance for a wide range of field seismic measurements. In relation to reservoir characterization, DAS has been applied to microseismic monitoring and analysis [31][32][33], hydraulic fracture monitoring [34][35] as well as in flow and production monitoring [36][37][38].

4. Deep Learning

Deep learning [39] is a branch of machine learning that has gained traction in the field of seismic data processing, analysis, and interpretation due to its computational efficiency, adaptability, and inherent ability to extract high-level features from recorded seismic waveforms with little to no manual engineering. Developed for pattern recognition in computer vision, deep learning models have high-level feature extraction mechanisms that enable them to transform raw data into a subset of feature vectors, allowing learning to take place. This makes them a perfect candidate for classification or regression tasks. The detection of seismic events is a classic example of a classification task, while inversion to locate the origin of the seismic energy can be considered as a multidimensional regression problem. The most popular deep learning architectures in seismology are recurrent neural networks (RNNs) and convolutional neural networks (CNNs). The latter is preferred for its processing speed and ability to handle large volumes of data; the former's ability to recognize sequential patterns in the data and use those patterns to predict the next possible scenario makes it the de facto time series analysis tool.

Because deep learning models are data-driven, they require a significant amount of data for training and validation. As a result, they are best suited to processing seismic data recorded by the DAS, which collects massive amounts of data. Binder and Tura [40] employed convolutional neural networks to automatically detect microseismic events in the data acquired by DAS along a borehole during a hydraulic fracture operation. They compared the results with those from a surface geophone array and observed that, despite the low SNR in the DAS data, the neural network was able to detect 167 new events that were not registered by the geophones. Huot et al. [41] reported a 98.6% accuracy of deep learning models trained with hyperparameters obtained by Bayesian optimization on 7000 manually selected microseismic DAS events. They concluded that by the application of AI, the model was able to predict more than 100,000 events, which enhanced the prediction of the spatio-temporal fracture developments, which otherwise could not have been detected by traditional methods. Furthermore, to overcome the problem of SNR that makes the data processing challenging, Qu et al. [42] introduced a new methodology based on fixed segmentation coupled with a support vector machine (SVM) model. The proposed methodology allowed for the identification of the best features and the optimal number of features required for producing accurate results. From the comparative analysis, the presented model had accurate results compared to the CNN and the short-term average and long-term average ratio (STA/LTA) conventional approach. Other applications of deep learning for the detection of seismic/microseismic activities are well-documented in [43][44][45][46].

Deep learning has also been applied to tasks other than the detection and classification of seismic activities. Wamriew et al. [47] demonstrated the potential application of deep learning to the inversion of microseismic data. They showed that a CNN model was capable of locating microseismic events and reconstructing the velocity model simultaneously in real-time from seismic waveforms. Tanaka et al. [48] employed a deep learning model to perform moment tensor inversion of acoustic emissions during a hydraulic fracturing experiment of granite rock and obtained 54,727 solutions.

Due to their computational efficiency, the models can be used in the field to process the data in real-time during its acquisition, thereby scaling down the amount of data to be stored while providing necessary information that could help optimize the field operations. Huot and Biondi [49], Wamriew et al. [50], and Huot et al. [51] emphasized that without the complete automation of microseismic data processing, large volumes of collected data could be wasted due to human processing limitations.

It is well-established in the literature that the active and real-time recording and processing of microseismic activities is very essential for the characterization of geological formations. Right from the exploration of the field to the appraisal, the development, production, enhanced, and improved oil recovery methods, abandonment well monitoring or utilization for the storage of CO_2 or H_2. In addition, the challenges of the physical processing of huge volumes of microseismic data and the limitations imposed could be overcome by the implementation of automated artificial intelligence models, as have been developed in recent times that could predict events and analyze the geological changes in reservoirs.

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