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Precursory Detection of Casing Deformation and Induced Seismicity in Unconventional Reservoirs via Real-Time Surface Pressure Data Analytics

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Abstract

Hydraulic fracturing operations in unconventional reservoirs can trigger a spectrum of subsurface deformation mechanisms, such as casing deformation, fracture-driven interactions (FDIs), and induced seismicity. These pose substantial risks to well integrity and nearby infrastructure. This paper introduces a field-proven, real-time analytics platform that utilizes surface pressure data to detect and categorize early indicators of these geomechanical events.

At the heart of the system is a proprietary signal decomposition technique that extracts and analyzes nonlinear, nonstationary acoustic energy features from surface wellhead pressure. By evaluating the evolution of resonant, stable, and chaotic energy components, the framework provides early classification of deformation modes and their likely source mechanisms. Its frame-based architecture supports sub-second data processing, allowing for uninterrupted real-time monitoring during fracturing operations.

Demonstrated in field trials across the Permian Basin, Eagle Ford, Uinta, Montney, and Duvernay formations, the system consistently identified high-risk intervals several hours ahead of traditional diagnostics such as microseismic events or caliper-confirmed deformation. Ongoing deployments in the Eagle Ford and Midland Basin continue to enhance the development of basin-specific geomechanical risk models.

Recent advancements incorporate this capability into a hierarchical machine learning architecture, integrating convolutional and transformer-based models to detect both short-term anomalies and long-term geomechanical patterns. Regional calibration further supports localized risk forecasting, enhancing predictive accuracy for issues like casing deformation and seismicity.

This approach effectively transitions surface pressure from a passive measurement tool into an active geomechanical surveillance system. It enables operators to shift from reactive event responses to predictive risk mitigation, improving development economics, safety, and stakeholder engagement, while supporting longer on-site activity through governed traffic light systems.

Introduction

Hydraulic fracturing has revolutionized hydrocarbon recovery in unconventional plays, unlocking production from low-permeability formations. However, these processes can also give rise to complex subsurface geomechanical challenges including FDIs, induced seismicity, and casing damage—that jeopardize operational success and wellbore integrity.

While tools like microseismic monitoring, distributed acoustic sensing (DAS), and caliper logs have been instrumental in understanding such phenomena, they are often constrained by high costs, limited spatial coverage, and post-event application. They typically capture failures only after they occur, limiting operators' ability to intervene in time.

Surface pressure data, in contrast, is available in real time, economical to collect, and inherently rich in information regarding subsurface activity. However, its utility has historically been limited by the signal's complexity—nonlinear, nonstationary behavior superimposed with operational noise and interacting phenomena make it difficult to interpret using conventional frequency-domain tools.

This paper presents a novel signal decomposition and machine learning framework that converts raw wellhead pressure data into a real-time geomechanical sensing system. Rather than treating pressure as a linear trace, the method reinterprets it as a dynamic acoustic energy spectrum, capable of revealing deformation-related behaviors in stable, resonant, or chaotic forms.

By monitoring the second-by-second structure of pressure impulses and classifying their acoustic characteristics, the system differentiates routine fracturing activity from patterns associated with subsurface instability, such as fault movement, fracture reactivation, or casing interaction.

The framework also incorporates a hierarchical machine learning model trained on multi-basin datasets and fine-tuned for basin-specific deployment. This real-time toolset enables identification, classification, and quantification of subsurface geomechanical risks. The paper details the architecture and shares findings from successful case studies in the Montney and Duvernay formations, as well as ongoing work in the Eagle Ford and Midland Basin. These results support the evolution of real-time early-warning systems and informed operational adjustments that can reduce cost and prevent geomechanical failures.

Theory and/or Methods

Surface Pressure Signal Segmentation:

The system begins with a univariate pressure time series collected from the wellhead during fracturing. While it supports standard acquisition frequencies (e.g., 1 Hz), it has been rigorously tested on high-resolution datasets reaching up to 50 Hz. Altogether, the system has processed 559,000 cumulative hours of data across more than 7.2 billion individual samples. The high-frequency data are especially valuable for capturing transient or fine-scale features linked to geomechanical activity.

To enable real-time analysis, the pressure signal is divided into short, overlapping time windows. Each frame acts as a discrete analysis unit within the decomposition pipeline. Macro and micro pressure characteristics are assessed for each frame, contributing to operational context classification. The architecture operates with sub-13 millisecond latency per frame and can evaluate approximately 12 hours of signal in under two seconds, supporting seamless real-time streaming during active completions.

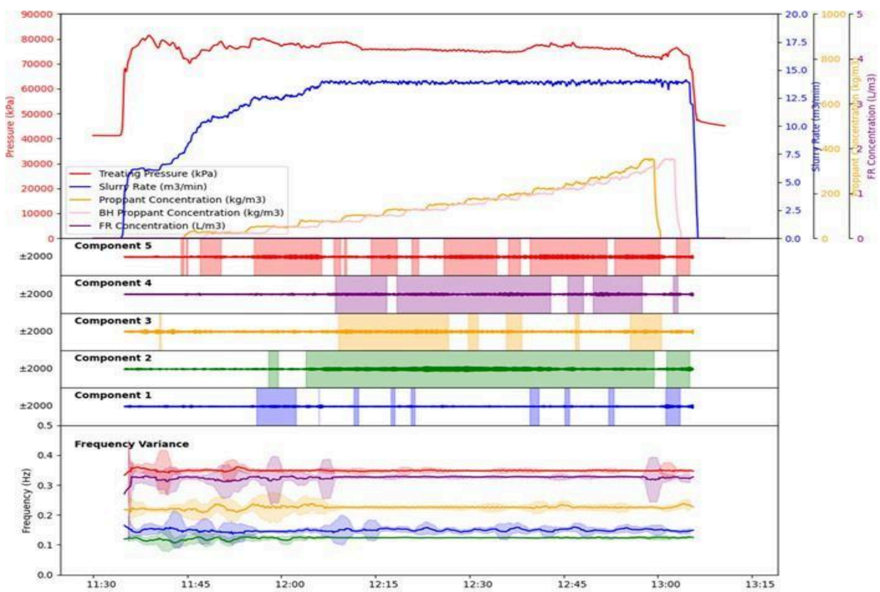

Figure 1 Pressure Signal Decomposition

Signal Decomposition and Characterization:

Every signal frame is analyzed using a patented decomposition algorithm tailored to the nonlinear and nonstationary nature of wellhead pressure. Unlike traditional spectral analysis methods such as Fourier transforms or spectrograms, this technique does not rely on predefined bases or time-window assumptions. Instead, it isolates localized oscillatory components that better reflect subsurface conditions.

The output is an energy-based interpretation of the signal, revealing its underlying impulse structure. Each energy mode is then classified into one of the following categories:

- **Resonant:** Periodic oscillations linked to stress cycling or echo phenomena.
- **Stable:** Low-variance signals typical of normal pumping behavior.
- **Chaotic:** High-entropy, broadband signals associated with unstable propagation or fault slip.

This classification enables quantification of energy types in each frame, allowing temporal tracking of subsurface activity. Unlike windowed frequency tools, this method maintains signal fidelity and enables the identification of localized deformation sources.

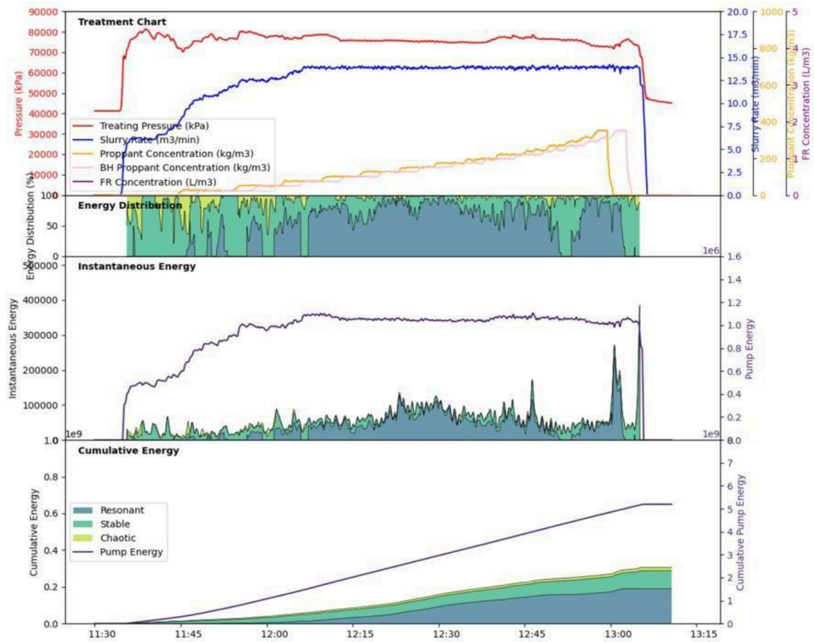

Figure 2 Pressure Signal Source Energy Representation

Feature Extraction and Behavioral Classification:
Following decomposition, each signal is further examined for:

- Energy envelope amplitude and duration
- Persistence of transient features (e.g., bursts, decays)
- Morphological signatures such as delayed decay, rapid onset, or modulated harmonics

These characteristics help flag atypical energy signatures, such as:

- Energy output anomalies relative to pressure input
- Abrupt shifts in response to pump schedule changes
- Resonant buildup indicating possible fault activation or slip

Frames are benchmarked against both regional and historical data. Statistically significant deviations trigger internal alerts, feeding directly into the machine learning risk classification system.

Predictive Modeling via Machine Learning:
The processed data streams are input into a multi-tier machine learning model optimized for real-time geomechanical event detection. The system comprises:

- **CNNs** for detecting frame-level morphological patterns in high-frequency data
- **Transformers** for identifying long-term behavioral sequences and temporal transitions
- **Class-specific classifiers** trained to identify casing deformation (CD), induced seismicity (IS), and FDIs

The training process follows a structured flow:

1. **Pretraining:** using data from various basins and operational settings
2. **Fine-tuning:** on basin-specific datasets to reflect local geologic and operational variability
3. **Calibration:** aligning model outputs with confirmed deformation and seismic events using caliper logs, MS arrays, and other validation tools

This architecture generates continuously updated risk probabilities during live completions, integrating both fast-changing signal patterns and broader geomechanical context.

Offset Well Cross-Correlation:
When multiple wells are monitored concurrently (e.g., in infill pads or zipper fracs), the system performs cross-signal analyses to detect synchronized anomalies. These may include:

- Simultaneous high-energy episodes
- Aligned resonant or chaotic trends
- Correlated impulse structures suggesting stress transfer or pressure migration

Such patterns suggest regionally connected deformation mechanisms, such as shared bedding plane activation or induced fault slip. These insights will support future enhancements in spatial risk mapping and completions planning, including optimized designs for parent-child mitigation.

Results

The decomposition and acoustic energy classification system has been applied in several field trials across North America to test its effectiveness in detecting early geomechanical signals. The outcomes detailed below highlight its ability to predict high-risk intervals ahead of validation by traditional diagnostics such as microseismic sensors, caliper logs, or incident reports.

Casing Deformation – Montney Formation (British Columbia, Canada)

Across multiple wells in the Montney Formation, the system detected anomalous energy behaviors prior to observed casing deformation. These were marked by:

- Persistent high-amplitude resonant energy observed during the treatment of several wells on a single pad.
- Unusual energy decay characteristics, including sudden spikes followed by consistent resonant amplitudes.
- Noticeable departures from regional baseline energy profiles established in nearby wells and earlier stages.

In numerous instances, the system's alerts preceded caliper-confirmed deformation events by several hours—up to full days in advance. In one particular case, an automated warning was delivered to the operator more than seven hours prior to caliper tool detection, enabling real-time response and stage plan reassessment.

Induced Seismicity – Duvernay Formation (Alberta, Canada)

With its elevated pore pressures and naturally fractured rock fabric, the Duvernay Formation presented an ideal environment to evaluate seismic risk detection. During the trial:

- A gradual buildup of low-frequency resonant energy was observed prior to slow energy release.
- The system flagged several high-risk intervals during pumping, marked by waveform irregularities and increased stable energy that aligned with loss of fracture isolation.
- Multiple flagged periods coincided with structural activations confirmed by surface and regional seismic arrays.

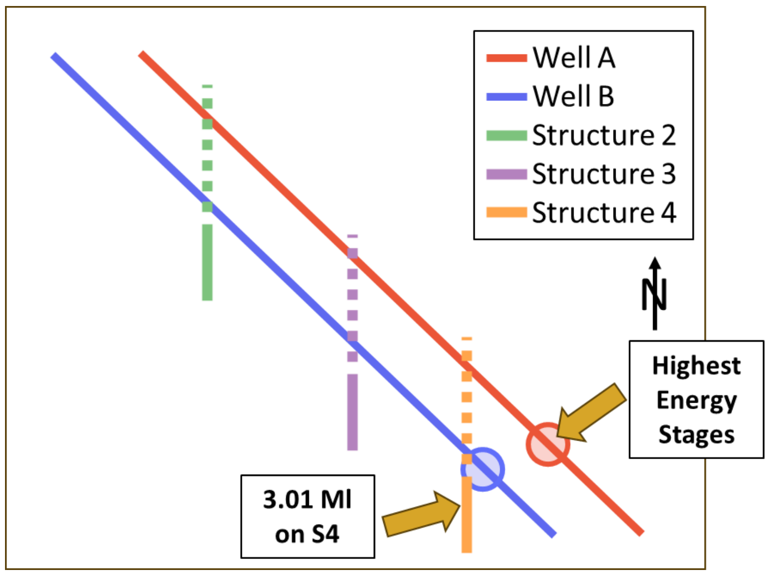

Figure 3 Wellbore Plan View with Structure Locations

During the treatment of Stage 57 in Well A, a high-resonance period was followed by a system-generated warning for potential M3+ seismic activity. Approximately 1.5 hours later, a 3.01 ML event occurred. This matched the timing and severity of the forecast, confirming the system's predictive reliability.

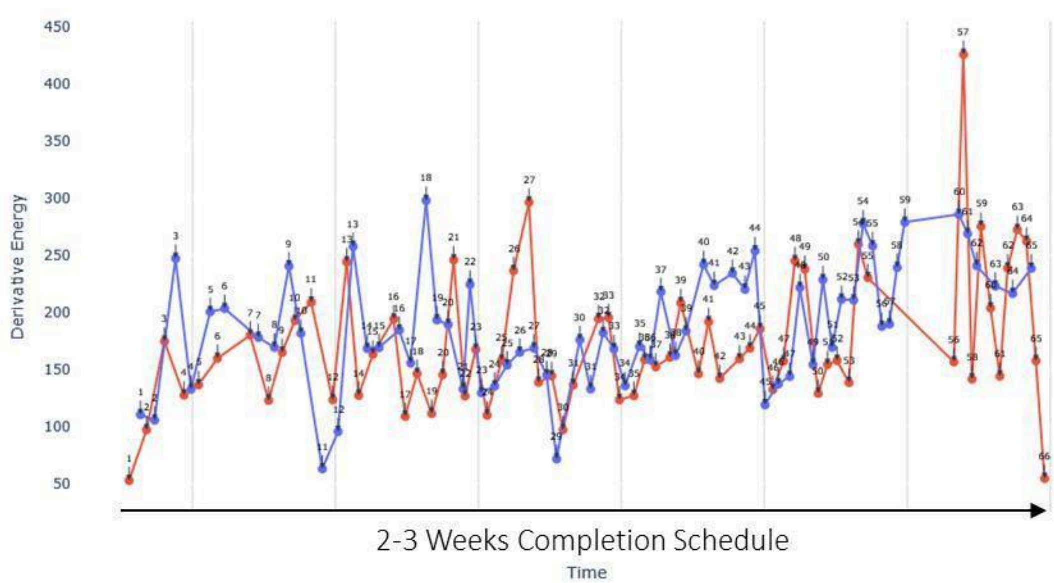

Figure 4 Derivative Energy for Duvernay Case Study

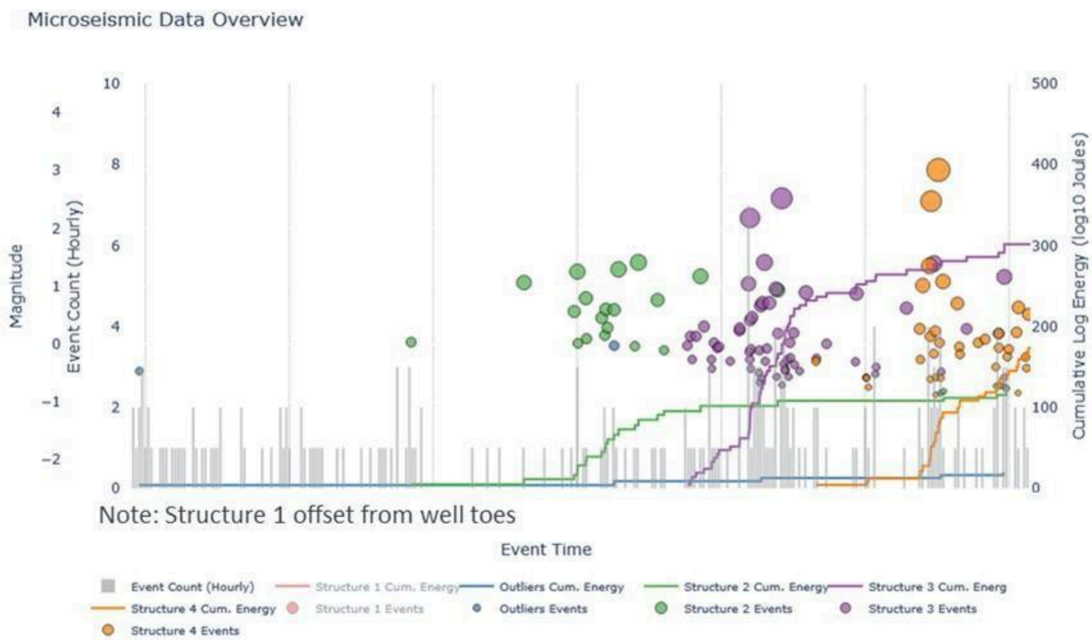

Figure 5 Seismic Events for Duvernay Case Study

Casing Risk Trends – Eagle Ford Shale (Texas, USA)

Ongoing deployments in the Eagle Ford are focused on building basin-specific thresholds for casing deformation risk. Preliminary findings include:

- Repeating high-resonance signal patterns suggesting cyclic loading or stress interaction.
- Unusual impulse morphologies, potentially associated with fractures approaching nearby faults.
- Pressure behavior variability driven by local geological and structural influences.

These observations are actively guiding calibration of Eagle Ford-specific risk models.

Seismicity Risk – Midland Basin (Texas, USA)

Trials in the Midland Basin aim to detect pre-seismic energy trends and their influence on production. Key findings include:

- Stage-over-stage buildup of low-frequency resonant energy.
- Confirmed alignment with microseismic events recorded by regional monitoring arrays.
- Recurrent deformation-like signals across multiple wells treated sequentially.
- Clear waveform distinctions based on fracture geometry and propagation style.

The insights are informing the development of real-time automated adjustments for completions optimization and seismic risk mitigation.

Discussion / Related Works

Historically, the identification of subsurface deformation during hydraulic fracturing has relied heavily on post-event diagnostics such as microseismic imaging, DAS, or caliper logging. While powerful, these tools are often reactive, expensive, or geographically limited, reducing their utility for real-time intervention.

This study establishes that surface pressure—when processed with advanced analytics—can function as a real-time proxy for subsurface behavior. Its accessibility and continuous availability make it uniquely suited for proactive risk management.

The core innovation lies in representing surface pressure as an evolving energy spectrum and classifying its components into resonant, stable, and chaotic energy modes. Each of these modes provides insight into physical phenomena such as fault slip, bedding-plane movement, or routine fracturing.

For example:

- A resonance spike followed by collapse may signal pressurization ahead of fault failure.
- Prolonged low-frequency signals could indicate bedding-plane slip or casing shear.
- Low-variance energy may suggest typical, non-risk behavior.

Unlike traditional frequency analyses (e.g., spectrograms), the system's patented decomposition preserves temporal resolution and impulse morphology, enhancing its ability to detect subtle anomalies.

Machine learning further enhances the system's classification accuracy. CNNs identify short-duration anomalies, while transformer models track longer-term shifts. Together, they enable distinction between operational noise and emerging risk patterns. Regional training ensures relevance across different basins, lithologies, and completions strategies.

Rather than replacing tools like microseismic or DAS, this framework complements them by:

- Providing early alerts that justify targeted instrumentation or response.
- Expanding coverage to less-instrumented fields.
- Offering live feedback during active pumping operations.

The ability to identify correlated behaviors across adjacent wells also supports future spatial risk models. With more high-frequency data and development of real-time geospatial inference, this framework could evolve into a basin-scale deformation mapping tool.

Conclusions

This work introduces a validated, real-time pressure analytics platform for forecasting subsurface geomechanical hazards during hydraulic fracturing. Using a proprietary decomposition approach, it reinterprets wellhead pressure as an evolving acoustic energy field, enabling high-fidelity detection of deformation and seismic precursors.

Key conclusions include:

- Surface pressure contains unique acoustic signatures that precede events such as casing deformation, FDIs, and induced seismicity—often hours before conventional confirmation.

- The system's frame-based architecture allows sub-second processing, enabling live monitoring of high-frequency data streams.
- Field validation across several basins confirms its ability to provide advanced warnings that support operational adjustments.
- The machine learning model—incorporating both CNNs and transformers—detects both short-term anomalies and long-term trends, with regional tuning improving accuracy.
- Identifying statistical and morphological outliers in pressure behavior allows operators to move from reactive to proactive geomechanical strategies.

Ultimately, this framework transforms surface pressure into a true real-time geomechanical sensing platform. As spatial resolution and data coverage grow, it will serve as a foundational tool for deformation monitoring, completions optimization, and operational risk reduction in unconventional plays.

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