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An integrated approach to characterize hydraulic fracturing-induced seismicity in shale reservoirs

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An Integrated Approach to Characterize Hydraulic Fracturing-Induced Seismicity in
Shale Reservoirs

by

Hui Gang

A THESIS

SUBMITTED TO THE FACULTY OF GRADUATE STUDIES
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ABSTRACT

There has been a remarkable increase in the induced seismicity, which is spatiotemporally related to the exploitation of the unconventional oil and gas reservoirs in the Western Canada Sedimentary Basin (WCSB) since 2013. Statistically, 6% of hydraulic fracturing (HF) operations targeting the Duvernay Formation are related to the induced seismicity with moment magnitude $M_L > 3$ in the WCSB. Many publications statistically established the spatial and temporal correlations between hydraulic fracturing and the induced seismicity events. However, the underlying mechanism on how the induced seismicity be triggered by the pore pressure diffusion and/or mechanical stress perturbation is still unclear, especially under the existence of the geology heterogeneity, reservoir geomechanics and fracturing fluid flow within the formation matrix and pre-existing natural faults and fractures networks.

In this study, an integrated approach of geology, geophysics, geomechanics and hydrodynamics is developed to characterize the hydraulic fracturing-induced seismicity in unconventional shale reservoirs. Firstly, a structural model including the faults and surfaces is developed by the multicomponent 3D seismic interpretation. The local structure attributes analysis and ant-tracking technique are then applied to identify the pre-existing faults and fractures distribution, where their distributions are calibrated by focal mechanism inversion of the mainshock events. Subsequently, a 3D geomechanical model is built, which incorporates the rock mechanics and in-situ stress regime into the structure model. Additionally, the hydraulic fracturing processes are simulated and hydraulic fractures geometry and fluid pressure distribution within the hydraulic fractures are estimated by history matching the net pressure. Finally, the fluid flow in hydraulic fractures

is coupled with the geomechanical model to characterize the pore pressure diffusion and poroelastic stress perturbation that causes the fault to slip.

We conclude that the proposed integrated approach can identify the triggering mechanisms of hydraulic fracturing-induced seismicity in tight and shale reservoirs. In the Mw 3.6 and Mw 4.1 cases, the poroelastic effects on high-permeable damage zones of a conductive-barrier fault are responsible for fault reactivation in the Precambrian Basement and top Winterburn Formation. Moreover, ant-tracking interpretation provides evidence to account for the spatial distribution of earthquake clusters during HF operations. The Mw 3.0 induced seismicity was triggered by fluid diffusion through hydraulic fractures along high-permeability fault damage zones downwards into the basement. This basal fault slip was attributed primarily to the elevated pore pressure along the fault plane in response to fracturing fluid injection.

Additionally, the ML 4.18 earthquake clusters were triggered by the hydraulic connection between stimulated wells and inferred fault. The controlling factors of such hydraulically induced seismicity are listed in the order of decreasing importance by HF-fault distance, fault permeability, injection rate, fault rigidity, injection layer permeability, and Biot's coefficient. Based on the in-depth investigation of eight field cases, five identified triggering mechanisms in the studied area, including (I) direct connection between hydraulic fractures and barrier-faults; (II) fault slip owing to downward pressure diffusion; (III) fault slip due to poroelastic stress perturbation; (IV) aftershocks of mainshocks; (V) natural fractures activation surrounding faults. Then, the mitigation strategy is proposed accordingly, including that (I) the east region of Fox Creek has been selected as the optimal fracturing region due to its low geological susceptibility; (II) The

proper real-time monitoring with downhole and/or surface microseismicity is required during and after HF operations in the west region; (III) Enlarging HF-fault distance and decreasing fracturing job size are also two practical approaches to reduce potential seismicity risks.

The integrated machine-learning approach suggests that ten geological, geomechanical, and operational parameters deriving from the integrated dataset of Fox Creek are included as input variables, whereas the maximum moment magnitude of each cluster is regarded as the target variable. Factors that mostly contributed to the induced seismicity are found to be the distance to fault, distance to Basement, minimum principal stress, cumulative injection volume, formation overpressure, number of fracturing stages, cumulative proppant placed, wellbore orientation and distance to Reef. Four machine learning approaches are evaluated, where Extra Tree has led to the highest coefficient of determination R^2 of 0.87. Case study results have shown that $M > 3$ induced seismicity can be potentially mitigated if it reduces the fluid injection volume by approximately 61.8% per well-pad.

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DEDICATION

To my dear parents, Zengliang Hui and Mei Li,

My beloved wife, Fei Gu

My dear daughter, Zeyue Hui

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CHAPTER 1 INTRODUCTION

1.1 Overview

High-quality oil and gas are trapped in the unconventional reservoirs in the Western Canadian Sedimentary Basin (WCSB), yet the traditional development operations cannot efficiently extract such hydrocarbons to the ground. The hydraulic fracturing technology is adopted to break the rock matrix and establish a high-permeable pathway between wells and the formation to obtain an economical production (Rubinstein et al., 2015). Generally, water and the mixture of chemicals and sands (i.e., proppant) is injected into these low permeable reservoirs. The fracturing fluids are first injected under high pressure to cause the tensile failure of rocks or reactivate existing fractures and create a fracture network (Warpinski et al., 2001). The proppant is then injected into the reservoir to keep the fractures open during the flowback and production process, which is essential to maintain the fracture conductivity and enhance the hydrocarbons production. In hydraulic fracturing operations, multistage hydraulic fractures are usually induced along the lateral section of the horizontal wells, drilled in particular directions from the same well pad. Typically, the magnitude of microseismic events induced by hydraulic fracturing varies from -4.0 to -1.0, which is determined by the fracturing operational parameters, formation and fluid properties, and the in-situ stress. However, events with a large magnitude may occur when the fracturing fluids are injected into the pre-existing natural fractures or faults. For example, several cases of induced seismicity caused by hydraulic fracturing operations in shale reservoirs have been reported in Western Canada (Atkinson et al., 2015; Schultz et al., 2015; Bao and Eaton, 2016; Schultz et al., 2020).

The induced seismicity related to hydraulic fracturing in the development of unconventional reservoirs has increased notably in North American, West Europe, East Asia in the last decade (Atkinson et al., 2016; Grigoli et al., 2017; Lei et al., 2019; Schultz et al., 2020). In the WCSB, the majority of induced seismicity have been attributed to wastewater disposal in the Brazeau River zone (Schultz et al. 2014), hydrocarbon production in the Strachan D-3A Field (Baranova et al., 1999), enhanced oil recovery in the Rocky Mountain House region (Wetmiller et al. 1986), and hydraulic fracturing (HF) in the Fox Creek area (Schultz et al. 2017; Hui et al., 2021a). Statistically, 6% of HF operations targeting the Duvernay Formation are related to the induced seismicity with moment magnitude $M_L > 3$ in WCSB (Ghofrani and Atkinson, 2020). The occurrence of some large magnitude HF-induced seismicity in WCSB has been linked to site-specific geological, geomechanical, and operational factors, including the proximity to basement and carbonate reef margins, formation overpressure, shale content and total organic content (TOC), critical stress state of seismogenic faults, the hydraulic connection between pre-existing faults and stimulated wells (Schultz et al., 2017; Pawley et al., 2018; Eaton and Schultz, 2018; Eyre et al., 2019; Zhang et al., 2019; Hui et al., 2021b).

1.2 Problem statement

Two major hypotheses have been proposed to understand the fundamental mechanisms of HF-induced seismicity, including pore pressure diffusion and poroelastic stress perturbation, which can decrease the fault strength and thus cause faults to slip (Ellsworth, 2013; Galloway et al., 2018; Healy et al., 1968; King and Deves, 2015). The pore pressure diffusion is regarded as the primary mechanism for HF-induced seismicity, which is controlled by the hydrological communication between wells and faults. The

second mechanism is the fault slip caused by the poroelastic stress transfer during fracturing fluid injection, which can transmit farther away from a stimulated well. McGarr (2002) further concluded that the stress transfer could trigger induced seismicity events(mainshock-aftershock). The spatiotemporal relationship between hydraulic fracturing (HF) with induced seismicity have been studied in the literature, demonstrating that the induced seismicity in the WCSB has been largely attributed to multistage hydraulic fracturing operations (Schultz, Mei, et al., 2015; Atkinson et al., 2016; Hui et al., 2021b).

Bao and Eaton (2016) pointed out that stress changes during operations can activate fault slip to a large offset distance, whereas pressurization by hydraulic fracturing into a fault yields episodic seismicity that can persist for months. Deng (2016) reported that the changes of poroelastic stress (instead of pore pressure) are the predominant reason for triggering the induced seismicity. Lele (2017) claimed that the earthquake was due to the direct connection between the hydraulic fractures and nearby faults, which caused the faults to slip and induced large seismicity events. However, few studies have comprehensively investigated the underlying mechanisms of the induced seismicity, especially combining the components of the reservoir heterogeneity, geophysics, geomechanics, and fluid dynamics. Therefore, an integrated approach is required to explore the triggering mechanisms that are responsible for the occurrence of HF-induced seismicity in the WCSB and further propose the corresponding mitigation strategy during the development of the unconventional tight/shale resources.

In this work, an integrated approach of geology, geophysics, geomechanics, and hydrodynamics is developed to characterize the hydraulic fracturing-induced seismicity in shale reservoirs. Firstly, a structural model including the faults and surfaces is developed

by the multicomponent 3D seismic interpretation. The local structure attributes analysis and ant-tracking technique are then applied to identify the pre-existing faults and fractures distribution, where their distributions are calibrated by focal mechanism inversion of the mainshock events. Subsequently, a 3D geomechanical model is built, which incorporates the rock mechanics and in-situ stress regime into the structure model. Additionally, the hydraulic fracturing processes are simulated and hydraulic fractures geometry and fluid pressure distribution within the hydraulic fractures are estimated by history matching the net pressure. Finally, the fluid flow in hydraulic fractures is coupled with the geomechanical model to characterize the pore pressure diffusion and poroelastic stress perturbation that causes the fault to slip. The integrated approach is applied to eight field cases to investigate the underlying triggering mechanisms of HF-induced seismicity in the WCSB. The improving understanding of such physical mechanisms would help propose the corresponding mitigation strategy to reduce the future seismicity risks in the WCSB.

1.3 Research Objectives

The primary objective of this dissertation is to develop a comprehensive approach that consists of geophysics, geomechanics, and hydrodynamics to understand the underlying triggering mechanisms, identify key controlling factors that contribute to the HF-induced seismicity and develop the associated mitigation strategy. Four specific objectives of this research are listed as follows.

- (1) Propose the integrated approach to characterize hydraulic fracturing-induced seismicity in shale reservoirs, where the structural modeling, geomechanics modeling, hydraulic fractures simulation, and coupled flow-geomechanics modeling are all combined together to characterize the HF-induced seismicity.

- (2) Apply the integrated approach to eight field cases to analyze the occurrence of HF-induced seismicity. Pressure diffusion and stress perturbation at the intersection of the faults and fractures will be studied by the coupled flow-geomechanics method to identify the different trigger mechanisms of induced seismicity due to hydraulic fracturing operations.
- (3) Identify key controlling factors that contribute to the HF-induced seismicity of field cases. The association of induced seismicity events with specific geological and operational conditions will be investigated from different field cases, and the dominant controlling factors triggering induced seismicity will be recognized during hydraulic fracturing operations.
- (4) Propose the mitigation strategy based on comprehensive risk management of induced seismicity. The potential risk of induced seismicity will be identified and mitigated by optimizing the selection of fracturing sites and managing operational factors to reduce the likelihood of inducing large events.

1.4 Outline

There are eight chapters in this thesis. Chapter 1 introduces the research background as well as the major research objectives. Chapter 2 presents an updated literature review on shale reservoirs, hydraulic fracturing and induced seismicity in unconventional reservoirs. Chapter 3 develops an integrated approach to characterize hydraulic fracturing-induced seismicity in unconventional shale reservoirs. Chapter 4 evaluates the applicability of the integrated approach on the Mw 3.6 and Mw 4.1 induced seismicity near the Crooked Lake region. Chapter 5 explores the controlling factors of hydraulic fracturing-induced

seismicity based on two field cases in Western Canada. Chapter 6 characterizes the induced seismicity and evaluates its susceptibility towards fracturing stimulations based on eight field cases in Fox Creek. Chapter 7 develops a comprehensive machine-learning approach to evaluate the susceptibility and mitigate the risks of hydraulically induced seismicity, as well as forecast the shale gas production via the integration of geological, geomechanical and operational factors in Fox Creek. Finally, conclusions of the primary research work and the proposed future work are listed in Chapter 8.

CHAPTER 2 LITERATURE REVIEW

2.1 Duvernay Shale Reservoirs

The shale gas, found in unconventional reservoirs, differs by its geological location and characteristics, which will affect the process, cost, and level of ease associated with gas extraction. Shale gas has migrated from a source rock and then trapped within an impermeable rock layer that circumvented it from flowing to the surface. In general, conventional natural gas can be easily explored and developed by drilling traditional vertical wells (Figure 2.1). Unconventional gas, including shale gas, is generally more difficult and also expensive to extract than conventional natural gas due to the high costs, which can range from \$3 million to \$9 million per well (Jed, 2014). Therefore, the lower full-cycle cost originates from the higher productivity of the shale gas wells since the new advanced technology allows for better access to the source rock from a single well pad (IHS Global Insight, 2011).

The world energy market has witnessed a significant increase in the production of unconventional reservoirs in recent years, such as the natural gas extracted from shale reservoirs. The top five countries with technically recoverable shale gas reserves are China, Argentina, Algeria, the US and Canada (Jed, 2014). Recently, Canada's natural gas industry has reported the discovery of large volumes of in-place and recoverable shale gas resources. In the WSCB, 15 prospective shale gas formations have been identified and five of these formations (Duvernay, Muskwa, Basal Banff/Exshaw, North Nordegg, and the Wilrich) may contain up to 1,291 trillion cubic feet (TcF) of gas-in-place. In 2014, Alberta produced 12518 petajoules (1015 joules) of energy from all sources, among which natural gas resources occupied a great proportion (AER, 2015).

Figure 2.1 Schematic diagram showing forming of shale gas (CAPP, 2018)

The Duvernay is an organic-rich shale-hosted formation and, depending on thermal maturity and position within the basin, produces natural gas liquids, or natural gas or oil (Switzer et al., 1994; Ronald et al., 2019). The Duvernay Formation is also commonly believed to be the primary source rock for the Devonian Leduc reef, Nisku, and Wabamun carbonate plays (Dunn et al., 2012). The Duvernay Shale reservoirs were deposited as organic-rich mudstone, a fine-grained rock that extends 130,000 square kilometers. The Total Organic Carbon (TOC) content of the Duvernay Formation covers the range of 0.1-11.1% (Rokosh et al., 2012). A net map in terms of the thickness of sediment was created by calculating a gamma-ray cutoff of >105 API. The map shows the dominance of shale in the West Shale Basin and much less shale, more carbonate instead, in the East Shale Basin (Figure 2.2). It is estimated that the Duvernay formation hosts approximately 61.7 billion barrels of oil and 11.3 billion barrels of natural gas (Schultz et al., 2015).

Figure 2.2 Net-shale isopach of the Duvernay Formation shale (Rokosh. CD et al., 2012)

2.2 Hydraulic Fracturing Techniques

High-quality oil and gas are trapped in the unconventional tight and shale reservoirs in the Western Canadian Sedimentary Basin (WCSB), yet the traditional development operations cannot efficiently extract such hydrocarbons to the ground. The hydraulic fracturing technology is adopted to break the rock matrix and establish a high-permeable

pathway between wells and the formation to obtain an economical production (Rubinstein et al., 2015). Hydraulic fracturing (HF) is the primary technology employed to extract shale gas or tight gas from unconventional reservoirs in Western Canada.

Generally, hydraulic fracturing techniques are coupled with more recent advances in horizontal drilling. During hydraulic fracturing operations, the wellbore is extended vertically downwards and horizontally for 1.0 ~ 3.0 km within shale reservoirs. Then large volumes of the mixture of chemicals and sands and water, called proppant, are injected under high pressure into low permeable reservoirs. The high-pressure fracturing stimulation creates additional permeability by generating an array of cracks (fractures) in the reservoir rocks (Economicdes et al., 2000). Multistage hydraulic fracturing creates hydraulic fractures that usually extend 100 ~ 200 meters. Normally, about one-quarter to one-half of the fluid mixture returns along the wellbore to the surface usually called fluid flowback.

Hydraulic fracturing in Canada was first invented in Alberta in 1953 to extract hydrocarbons from the biggest conventional oil field in Alberta-the giant Pembina oil field, which would have produced very little oil without fracturing (EDAC, 2018). Since then, more than 200,000 wells in Canada have been horizontally fracked for shale reservoir production, primarily in Western Canada. The productivity of horizontal wells in the Cardium, Duvernay, and Viking formations in Alberta, Bakken formation in Saskatchewan, Montney, and Horn River Formations would not be possible without hydraulic fracturing technology (NEB, 2011).

Specifically, more than 606 horizontal wells have been drilled in the Duvernay formation in the Fox Creek region (geoLOGIC database) and statistics of these fracturing

parameters are shown in Figure 2.3. These multistage horizontal wells performing hydraulic fracturing operations had an average injection rate of 9.4 m³/min, an average pressure of 62.6 MPa and a total average injection volume of 1200 m³ (Schultz et al., 2017). The pumped proppant and injected volume per well during hydraulic fracturing are increasing year by year, reaching the peak during recent years. Since the year 2013, several induced seismicity events with a magnitude larger than 3.5 due to hydraulic fracturing operations in the Duvernay formation have been reported (Altkinson et al., 2016; Bao and Eaton, 2016; Schultz et al., 2015).

Figure 2.3 Statistics of treatment parameters of fracturing horizontal wells targeting the Duvernay formation

2.3 Induced Seismicity in Western Canada

Recently, induced seismicity has attracted remarkable attention around the world. Industrial operations such as mining, oil and gas field depletion, hydraulic fracturing, wastewater injection, geothermal systems operations and impoundments of reservoirs can cause induced seismicity (Ellsworth, 2013; Grigoli et al., 2017). Figure 2.4 shows the global distribution of anthropogenic seismicity in conjunction with several industrial activities. It is noted that several earthquakes with large magnitudes have been reported in North America, Southern China, the United Kingdom, and Switzerland, which are spatiotemporally correlated with hydraulic fracturing (HF) operations in unconventional resources (Schultz et al., 2020; Lei et al., 2017; Bao and Eaton, 2016; Eyre et al., 2019). In North America, several induced clusters with magnitude larger than 4.0 are linked to hydraulic fracturing (e.g., $M_w=4.4$, Fox Creek, Canada) and wastewater injection (e.g., $M_w=5.6$, Oklahoma, USA). In this work, the moment magnitude (M_w) of earthquakes is derived from the focal mechanisms of earthquakes, whereas the local magnitude (M_L) of an earthquake is sourced from the public report detected by the seismology stations.

Figure 2.4 Induced and triggered seismicity observed worldwide in conjunction with several industrial activities, which indicates the global distribution of anthropogenic seismicity and the maximum magnitude reported at each site (Grigoli F, 2017).

In the last decade, there has been a marked increase in induced seismicity due to the unconventional oil and gas exploration in WCSB and the central US (Atkinson et al., 2016). Recent studies suggest that industrial operations during oil and gas oilfield development, such as hydraulic fracturing and wastewater injection, are two major causes of induced seismicity in the WCSB and central US (Atkinson et al., 2016). Evidence shows that most induced events, especially with Mw larger than 3.0, occurred in the central US are largely attributed to wastewater injection (Ellsworth, 2013; Frohlich et al., 2014; Keranen et al., 2013; Rubinstein and Babaie Mahani, 2015; Weingarten et al., 2015). In contrast, shreds of evidence have shown that hydraulic fracturing operations are closely related to the most recent induced seismicity temporally and spatial in Western Canada

(Atkinson et al., 2015; Schultz et al. 2015; Bao and Eaton, 2016), such as the clusters of induced seismicity with a maximum magnitude of Mw 3.6, between October 25 and December 15 in 2016 in the Fox Creek area, Alberta (Eaton et al., 2018), the earthquake with a magnitude of Mw 4.5 on November 29, 2018, in the Fort St. John region, British Columbia (Natural Resources Canada, 2018) and the earthquake with a magnitude of Mw 4.18 on March 4, 2019, near Red Deer region, Alberta. Figure 2.7 illustrates the seismicity and wells in the Western Canada Sedimentary Basin (WCSB). It can also be found that the induced seismicity in the WCSB has increased sharply since 2009, corresponding with a large increase in the numbers of horizontal wells performing hydraulic fracturing operations (Atkinson, 2016).

Figure 2.5 Historical recorded seismicity up to 2020/01/31 in Western Canada (Hui et al., 2021b). Red circles denoted earthquake clusters with M_w larger than 2.5. The beach balls show the focal mechanisms of tectonic-related (green), HF-induced (red), and EOR-induced (blue) events (Schultz et al., 2017; Wang et al., 2018). The blue dashed line shows the deformation margin of the Rocky Mountains.

2.4 Triggering Mechanisms of Induced Seismicity

Two major hypotheses have been proposed to understand the fundamental mechanisms of HF-induced seismicity, including pore pressure diffusion and poroelastic stress perturbation, which can decrease the fault strength and thus cause faults to slip (Ellsworth, 2013; Galloway et al., 2018; Healy et al., 1968; King and Deves, 2015). The pore pressure diffusion is regarded as the primary mechanism for HF-induced seismicity, which is controlled by the hydrological communication between wells and faults. The second mechanism is the fault slip caused by the poroelastic stress transfer during fracturing fluid injection, which can transmit farther away from a stimulated well. Figure 2.6 illustrates the schematic diagram showing the triggering mechanisms of HF-induced seismicity.

Figure 2.6 Schematic diagram showing mechanisms of fluid-induced seismicity (Ellsworth, 2013)

2.4.1 Changes of Pore Pressure and Poroelastic Stress during hydraulic fracturing

During hydraulic fracturing operations, fracking fluid with proppant is injected through the wellbore at a high injection rate and pressure. It is well known that when the fracking fluid pressure exceeds the minimum principal stress and tensile strength of reservoir rocks, hydraulic fractures will propagate within the fracking reservoir zone (Gandossi et al., 2015). If hydraulic fractures propagate and connect with the pre-existing fault, fluid in hydraulic fractures will increase the pore pressure of the fault, which will reduce the normal stress on the fault plane and move the fault towards the Coulomb failure criterion (Figure 2.7a). In this case, pressure diffuses rapidly through the pre-existing fractures and faults at diffusion rates that can exceed 1km/day (Tadokoro et al., 2000).

The pore pressure increase due to fluid injection can also lead to an increase of the rock mass volume, which will change the regional stress regime of faults. The vertical stress is determined by the pressure change and Biot's coefficient, while the horizontal principal stress change is related to the Poisson's ratio of rocks and is relatively smaller than that of vertical stress (Soltanzadeh, 2009). In this scenario, the Mohr circle of stress shrinks during fluid injection (Figure 2.7b). When the poroelastic stress path converges onto the Coulomb failure criterion, faults can also be reactivated during hydraulic fracturing.

Figure 2.7 Effects of pore pressure perturbations and poroelastic stress changes on fault failure. (a) An increase of pore pressure reduces the normal stress on the fault plane and moves the fault towards the Coulomb failure criterion. (b) Poroelastic stress changes lead to the shrink of the Mohr circle of stress (Keranen, 2018).

2.4.2 Mainshock-aftershock effects

The Coulomb stress change discussed in the previous section can also describe most aftershock events following large earthquakes (King et al., 1994; King and Deves, 2015). This is because, during fault slips in one large event, the rock surrounding the fault will deform elastically. Consequently, the local stress around the fault will change, with some regions experiencing a positive Coulomb stress change while others are experiencing a negative Coulomb stress change. In areas experiencing positive Coulomb stress changes, the fault state will move towards a critically stressed state, which increases the potential of fault reactivation and induced aftershock events (Steacy et al., 2005; Wassing et al., 2014).

For example, the Landers earthquake in 1992 with Mw 7.3 was triggered by reactivation of strike-slip type faults, with fault rupture length extended about 70 km. The Mw 6.5 Big Bear earthquake occurred after the mainshock, which was exactly located in the positive Coulomb stress change area (King and Deves, 2015). As is shown in Figure 2.8, the Big Bear earthquake was triggered by approximately positive 2 bars (0.2Mpa) of Coulomb stress change after 3 hours following the mainshock.

This case demonstrates that the Coulomb stress change due to a mainshock event can trigger the occurrence of aftershock events. King (2015) concludes that the positive Coulomb stress change by 0.05 Mpa is sufficient to trigger aftershock events. The location and magnitude of aftershocks depend on the pre-existing fault orientations and initial stress states (Zhao, 2018).

Figure 2.8 The calculated Coulomb stress change caused by the Landers and Joshua Tree earthquake before the occurrence of the Big Bear shock. The Mw 6.5 Big Bear earthquake occurred after this Mw 7.3 mainshock, which located the positive Coulomb stress change of 0.2 Mpa (King and Deves, 2015).

2.5 Induced Seismicity Characterization and Its Controlling Factors

There are many previous publications establishing the spatiotemporal relationship between hydraulic fracturing (HF) and induced seismicity in recent years, providing solid evidence that reported cases of induced seismicity in the WCSB had been largely attributed to multistage hydraulic fracturing operations (Eaton and Babaie Mahani, 2015; Schultz et al., 2015; Atkinson et al., 2016). Bao and Eaton (2016) studied the patterns of seismicity and concluded that stress changes during HF treatment could cause fault slip to an offset distance of >1 km, whereas pressurization by HF operations into a fault yields episodic seismicity that can persist for months (Figure 2.12). Deng (2016) calculated the changes of stress and pore pressure caused by nearby HF operations via a linear poroelasticity approach and demonstrated that the spatial distribution of the December 2013 seismicity sequence is consistent with modeled positive Coulomb stress change. Lele (2017) used the finite element model in a low permeability homogeneous medium to investigate the causes of induced seismicity. He proposed an alternative mechanism, that is, the direct connection between the hydraulic fractures and nearby faults caused the faults to slip and induced larger seismicity events. However, few studies have comprehensively investigated the underlying mechanisms of the induced seismicity, especially combining the components of the reservoir heterogeneity, geophysics, geomechanics, and fluid dynamics.

The controlling factors of HF-induced seismicity have also been studied in the literature. Based on previous studies, the occurrence of some large magnitude HF-induced seismicity in WCSB has been linked to site-specific geological, geomechanical, and operational factors, including a large amount of fracturing fluid injection (Schultz et al., 2018), the proximity to pre-existing faults (Pawley et al., 2018); the proximity to basement

and carbonate reef margins (Pawley et al., 2018; Schultz et al., 2017), and formation overpressure (Eaton and Schultz, 2018).

Specifically, Schultz et al. (2018) explored relationships between injection parameters and seismicity response based on a hydraulic fracturing database. He concluded that the induced seismicity events in Fox Creek are closely linked to the fracturing operations that used a large amount of the injection volumes (10^4 to 10^5 m³). Pawley et al. (2018) trained a machine-learning algorithm to systemically evaluate tectonic, geomechanical, and hydrological proxies suspected to control induced seismicity. It was found that the top four paramount parameters that contribute to HF-induced seismicity are proximity to Basement, in situ stress, proximity to reef margins, and lithium concentration. Eaton and Schultz (2018) investigated the relations between formation overpressure and induced seismicity and concluded that anthropogenic pore-pressure increase and proximity to critically stressed faults, high in situ overpressure of shale formations might also represent a controlling factor for HF-induced seismicity.

2.6 Summary

- (1) The Duvernay is an organic-rich shale-hosted formation and, depending on thermal maturity and position within the basin, produces natural gas liquids, or natural gas or oil. The Duvernay Formation is also commonly believed to be the primary source rock for the Devonian Leduc reef, Nisku, and Wabamun carbonate plays. It is estimated that the Duvernay formation hosts approximately 61.7 billion barrels of oil and 11.3 billion barrels of natural gas.
- (2) The hydraulic fracturing technology is adopted to break the rock matrix and establish a high-permeable pathway between wells and the formation to obtain an economical production. Hydraulic fracturing (HF) is one of the primary technologies employed to extract shale gas or tight gas from unconventional reservoirs. More than 606 horizontal wells have been drilled in the Duvernay formation in the Fox Creek region, showing a great application in the development of unconventional reservoirs in the WCSB.
- (3) Many earthquakes with large magnitudes have been reported in the WCSB, which are spatiotemporally correlated with hydraulic fracturing (HF) operations in unconventional resources. The HF-induced seismicity in the WCSB has increased sharply since 2009, corresponding with a large increase in the numbers of horizontal wells performing hydraulic fracturing operations.
- (4) Two major hypotheses have been proposed to understand the fundamental mechanisms of HF-induced seismicity, including pore pressure diffusion and poroelastic stress perturbation, which can decrease the fault strength and thus cause faults to slip. The pore pressure diffusion is regarded as the primary mechanism for

HF-induced seismicity, which is controlled by the hydrological communication between wells and faults. The second mechanism is the fault slip caused by the poroelastic stress transfer during fracturing fluid injection, which can transmit farther away from a stimulated well.

CHAPTER 3 AN INTEGRATED APPROACH TO CHARACTERIZE THE HYDRAULIC FRACTURING-INDUCED SEISMICITY¹

Abstract

There has been a remarkable increase in induced seismicity in Western Canada and the majority of these events can be related to hydraulic fracturing operations applied to develop unconventional reservoirs. The underlying mechanism of such induced seismicity is still unclear and needs to be investigated to mitigate the risks of future events. In this paper, we propose a new integrated approach to characterize hydraulic fracturing-induced seismicity. Inferred faults in the target area were first identified by the ant-tracking approach and hydraulic fractures were characterized by simulating hydraulic fracturing processes. The coupled flow-geomechanics modeling was then performed to compute the Coulomb Failure Stress and determine the reactivation of pre-existing faults. A case study was finally utilized to demonstrate the applicability of the integrated method. Four north-south-oriented faults were interpreted and half-length of hydraulic fractures were calculated from 84 to 127 m. The calculated results of the flow-geomechanics model were in good agreement with the actual induced seismicity spatially and temporally. Three types of triggering mechanisms were accounted for HF-induced seismicity, including hydraulic fractures propagation, the connection between hydraulic fractures and a fault and connections of hydraulic fractures with the natural fractures around the fault. The injection rate could be decreased to mitigate risks of future seismic events.

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3.1 Introduction

There has been a remarkable increase of induced seismicity in the Western Canada Sedimentary Basin (WCSB) since 2009 when horizontal drilling and multistage hydraulic fracturing technologies were adopted to develop the shale reservoirs in WCSB (Atkinson et al., 2016). It is believed that some large induced seismicity events can be related to multistage hydraulic fracturing operations (Schultz et al., 2017). For example, the maximum magnitude M_w 4.1 event on Jan. 12 in 2016 near Crooked Lake area in Alberta, the M_w 3.2 event on Nov.25 in 2016 near Fox Creek area in Alberta, and the M_w 4.5 event on Nov. 29, 2018, near the Fort St. John region in British Columbia were all linked to nearby hydraulic fracturing operations (Eaton et al., 2018).

During hydraulic fracturing operations, a large amount of fluids is injected under high pressure to create fractures, which can be monitored by microseismic events. However, a higher moment magnitude of seismic events will occur if hydraulic fractures propagate into nearby faults or large natural fractures. The fundamental mechanisms of induced seismicity triggered by hydraulic fracturing operations include an increase in the fluid pressure and/or changes in stress, which further lead to the reactivation of existing faults (Healy et al., 1968; Raleigh et al., 1976). It is well known that when the injection pressure of the fracturing fluid exceeds the minimum principal stress and tensile strength of reservoir rocks, hydraulic fractures will propagate and generate a fractured reservoir zone. If hydraulic fractures propagate and connect with the pre-existing fault, fluid in hydraulic fractures will increase the in-situ pore pressure and reduce the normal stress on the fault plane. In this case, pressure diffuses rapidly through pre-existing faults at diffusion rates that can exceed 1.0 km/day and cause the fault to slip (Tadokoro et al., 2000). Bao

and Eaton (2016) studied the seismicity events patterns and concluded that the stress changes during the fracturing operations could activate the fault and cause it to slip to a long offset distance. But his research ignored hydraulic fracture geometries and the real-time fluid pressure changes within hydraulic fractures. Deng et al. (2016) calculated in-situ stress and pore pressure perturbations by assuming hydraulic fractures as a point source injection rather than the actual geometry of the hydraulic fractures. Lele et al. (2017) built a conception model and claimed that the induced earthquake was due to the direct connection between hydraulic fractures and nearby faults, which caused faults to slip and triggered large seismicity events. Fan et al. (2016) evaluated induced seismicity by integrating the geological, seismological and geomechanical analysis and emphasized the importance of detailed geomechanical site characterization for robust fault stability assessment prior to fluid injection.

In summary, there are no research studies in the literature to comprehensively investigate the underlying mechanisms of induced seismicity for specific cases, especially considering the effects of the reservoir geology, geophysics, geomechanics, and hydrodynamics (Atkinson et al., 2016; Lele et al., 2017). An integrated approach is required to explore trigger mechanisms that are responsible for the occurrence of HF-induced seismicity in shale reservoirs and further prevent such seismic events from happening during the development of the unconventional tight/shale resources. In this study, an integrated approach that combines geology, geophysics, geomechanics, and hydrodynamics was proposed and applied to the ToC2ME field case to explore the underlying trigger mechanisms to characterize hydraulic fracturing-induced seismicity in shale reservoirs.

3.2 Methods

Figure 3.1 depicts the flow chart of the integrated method proposed in this study. Firstly, the structure attributes analysis and ant-tracking technique were applied to identify the natural fault distribution and develop the structural model. A 3D geomechanical model was then built by introducing the rock mechanics and in-situ stress regime into the structure model. Hydraulic fracturing processes were simulated to calculate the fracture geometry and fluid pressure distribution, which was further verified by history matching the net pressure during fracturing operations. Finally, the fluid flow in hydraulic fractures was coupled with the geomechanical model to determine whether the interpreted faults were activated and the trigger mechanisms of the induced seismicity.

Structure Modeling. The availability of multicomponent 3D seismic data provides a good opportunity for exploring the possible relationship between induced seismicity events and structural features. Faults with large vertical offsets can be easily detected and interpreted due to their conspicuous structural discontinuities in the seismic profile, while faults with small vertical offsets (several meters) in the WCSB were often displayed as structural hinge lines rather than horizon terminations or recognizable offsets. The swarm intelligence of ant tracking was used to track small-offsets faults by following the discontinuities via populating a preprocessed 3D seismic data, which were further calibrated by the focal mechanism inversion of the microseismic events to build the structural model.

Geomechanical Modelling. Rock mechanical properties (e.g., Young's modulus and Poisson's ratio) at the well sites were calculated from well-logging data and properties between the wells were interpreted by inverting elastic modulus from the 3D seismic data. A deterministic modeling method was applied to build the rock geomechanics model. The

in-situ stress regime was then introduced into the model, which includes the minimum horizontal stress (S_{Hmin}), the maximum horizontal stress (S_{Hmax}), vertical stress (S_v), as well as the initial pore pressure (P_p).

Hydraulic Fracturing Simulation. Hydraulic fracturing processes were simulated via the previous geomechanical model to characterize hydraulic fractures geometry along the horizontal wellbores, such as fracture half-length, height, and conductivity. Real-time treatment data were collected from the field and utilized to determine the fracture properties by history-matching the net pressure during the stimulation operations.

Coupled Modelling of Fluid Flow and Geomechanics. The finite element approach was applied to develop the coupled model of the reservoir, which includes poroelastic calculation and the fracturing fluid flow behavior in the fractures and reservoir matrix. Such a model was then employed to study the pressure and stress changes and calculate the Coulomb Failure Stress (CFS) along the fault planes. Potential activation of the faults and the trigger mechanisms of the induced seismicity can be determined based on the CFS criteria.

Figure 3.1. Flow chart of the integrated approach to characterize induced seismicity

3.3 Case study

3.3.1 Field background

The Tony Creek Dual Microseismic Experiment (ToC2ME) conducted in the west of Fox Creek, Alberta, was employed to demonstrate the applicability of the integrated approach, as shown in Figure 3.1. Hydraulic-fracturing operations of a four-well pad were monitored by an array of sixty-nine shallow borehole geophone systems and two surface three-component geophones, spanned from 25 October to 15 December 2016. Details of data acquisition and processing can be found elsewhere (Eaton et al., 2018). These wells were targeted in the Duvernay Formation, which was deposited with the organic-rich shale in the late Devonian age (Creaney et al., 1990). The depths of the wells were about 2,500 m below the sea level (SSTVD) with a true vertical depth of 3,400 m, and the thickness of the Formation is about 40 m. The shale play has an average effective porosity of 6.6% and

an average total-organic-carbon (TOC) content of 4.5% (Ronald et al., 2018). Four horizontal wells, Well A, B, C, D from east to west, were drilled in a north-south orientation.

During the monitoring of HF operations, 4083 seismic events with a maximum magnitude of 3.2 were detected by the regional seismological network, among which 12 events were larger than 2 in magnitude. Figures 3.2a and 2b illustrate the spatial and temporal view of induced seismicity events, which were grouped into seven different clusters. Cluster 1, 3, and early parts of clusters 2 and 4 were less than 1.5 in magnitude, which occurred during the fracturing operations of well C. These events exhibited a series of northeast-southwest lineament orientations. Cluster 5 was similar to cluster 4 but with shorter lineament distribution, including an event with a magnitude of 2.67. After the completion of well C, the zipper-fracturing pattern operations were performed on the remaining horizontal wells A, B, and D. Cluster 6 was activated in Northeast lineament distribution at an offset of over 700 m from well A. Then, the later parts of clusters 2 and 4 were reactivated with a maximum magnitude of 3.2 and 3.12. By the end of fracturing operations on well A, cluster 7 occurred with a magnitude of less than 0.5.

Previous research on other HF-induced seismicity events in the Duvernay Formation has suggested that the larger events usually resulted from the reactivation of faults located in the Precambrian Basement below the formation (Bao & Eaton, 2016; Schultz et al., 2015). However, in this ToC2ME case, most of the larger induced seismicity events occurred above the Precambrian Basement, mainly within or above the injection layer, as shown in Figure 3.2b. The underlying trigger mechanisms for this case need to be investigated by conducting the integrated research mentioned in the methodology.

Figure 3.2. Spatial and temporal view of events and daily observation. (a) Map view of event epicenters colored by time and scaled by magnitude. The base map shows the elevation of the top Duvernay Formation. Cluster 1-7 were grouped by order of induced seismicity events. The map inside showed the location of the study area. (b) Profile of events epicenters in terms of depth below the sea level (SSTVD). Cluster 1 occurred beneath, and clusters 2-7 occurred above or within the Duvernay Formation. (c) Induced seismicity events observed per day. The histogram indicates the frequency of events per day. A double-headed arrow denoted the time range of event clusters. Triangles showed four large events ($M_w>3$). The vertical dashed line suggests the end of well C fracturing operations.

3.3.2 Natural faults identification and hydraulic fracturing simulation

The b value represents the slope of the semi-logarithmic magnitude versus frequency distribution and can be used to distinguish fault reactivation-induced events from HF-induced events (Gutenberg & Richter, 1944). Typically, events due to the reactivation of natural fractures and faults are characterized by $b < 1$, whereas hydraulic fracturing-induced seismic events are characterized by a relatively large value of $b > 1.5$ (Burridge & Knopoff, 1967; Eaton et al., 2014). Figure 3.3 illustrates the histograms and cumulative features of magnitude distribution for clusters 1-7. According to the criteria of b value, clusters 1, 3, 7 and the early part of cluster 2 were associated with the propagation of hydraulic fractures ($b \geq 2.21$), whereas clusters 4, 5, 6 and later part of cluster 2 were linked to the reactivation of natural faults and fractures ($b \leq 1.29$). This preliminary result was obtained based on the statistical analysis of induced seismicity events. An extensive analysis of the seismic and treatment data was further conducted to characterize natural faults and hydraulic fractures and understand the trigger mechanisms of induced seismicity in the study area.

Figure 3.3. Histograms and cumulative features of magnitude distribution for clusters 1-7. The legend shows the b value and sample numbers for each cluster. Two-time frames are shown in Clusters 2, 3, 4 by the reactivation sequence of related clusters.

(1) Identification of natural faults and fractures

Previous inversion work of 3D seismic data in the study area by Weir et al. (2018) and Eaton et al. (2018) failed to show a clear spatial correlation between the interpreted faults and induced seismicity events. In this work, the ant-tracking approach was selected to provide insights into structural features that might account for the induced seismicity events (Pedersen et al., 2002). The ant-tracking workflow includes seismic conditioning, edge detection, edge enhancement, and interactive interpretation. The results of the corresponding faults by the ant-tracking are shown in Figure 3.4. It can be seen that four major faults (Fault 1, Fault 2, Fault 3 and Fault 4) penetrated the Duvernay formation and two natural fractures (NF1, NF2) were interpreted by this approach and were in good agreement with the lineament features of events clusters (Figure 3.4a). The extension scale of natural fractures was less than that of major faults. The major faults developed from -2650m to -2100m (below sea level), while the heights of natural fractures were less than 100m. In addition, natural fractures tended to be controlled by regional in-situ stress and generally followed S_{Hmax} orientation (NE 45°), whereas major faults were restrained by the multi-stage paleostress regime and their directions were often not unidirectional. Figure

3.4a further depicted the spatial distribution of interpreted faults and clusters 2, 4, 5, 6. It demonstrated that they were directly linked to each other. The distribution of these faults and their properties could also be verified by the focal mechanism inversion of microseismic events (Zhang et al., 2019), as shown in Figure 3.4b. The source mechanisms of group 1 (clusters 4, 5 and later part of cluster 2), group 2 (clusters 1, 3, 7 and early part of cluster 2), group 3 (cluster 6) indicated the natural fault orientations of $3.9^\circ \pm 1.8^\circ$, $23.9^\circ \pm 3.3^\circ$, $28.2^\circ \pm 8.3^\circ$, respectively. The orientations of group 1 and group 3 in Figure 3.4b exhibited a high degree of consistency with interpreted faults.

Figure 3.4. (a) 3D view of interpreted natural faults by ant tracking approach. Event symbols were scaled by moment magnitude and colored by the date of occurrence. The color of inferred faults denoted the elevation of faults. (b) Focal mechanism inversion of induced seismicity events. Clusters 4, 5, and part of cluster 2 exhibited nearly north-south features, while clusters 1, 3, 6, 7, and part of cluster 2 displayed the lineament of northeast orientation (Edited from Zhang et al., 2019).

(2) Propagation of hydraulic fractures

Clusters of microseismic events due to fracturing operations can be used to monitor the geometry of hydraulic fractures. Hydraulic fractures propagate parallel to the maximum horizontal stress (S_{Hmax}) in the absence of faults or natural fractures. This propagation process was usually accompanied by microseismic events with a low magnitude M_w and a high b value. In this case, only clusters 1, 3, 7, and the early part of cluster 2 displayed the features of hydraulic fracturing propagation shown in Figure 3.3 ($M_w < 1.5$, $b \geq 2.21$). In this

work, the fracture half-length was determined by history-matching the net operational pressure during the fracturing operations via FracPro software. More specifically, the real-time treatment data were collected, including the treatment pressure, dead string pressure, slurry rate, and proppant concentration, together with the wellbore structure, heat conduction, and formation parameters to better simulate the fracturing process under reservoir conditions. Then, the fracturing fluid and proppant type were utilized to calculate the friction loss, closure pressure, and net pressure. Finally, the history matching of the net pressure can be performed to simulate the propagation of hydraulic fractures and determine the fracture half-length, as shown in Figure 3.5.

The simulation results suggested that the average half-length of hydraulic fractures for well A, B, C, D was 127.5, 117, 84.1, 102.1 m, as shown in Table 3.1. The height of hydraulic fractures was set the same as the thickness of the Duvernay Formation. These hydraulic fracture properties would be introduced into the coupled flow-geomechanics model. We also analyzed clusters 1, 3, and 7, which were closely linked to fracturing operations temporally and spatially. The spatial distribution of these clusters suggested that hydraulic fractures propagated with a half-length range of 100~160 m, which verified the reliability of HF simulation results. Therefore, the fracture and fault network in the study area was generated by combining hydraulic fractures with interpreted natural faults and fractures, which lay a foundation for the analysis of trigger mechanisms of induced seismicity in this case.

Figure 3.5. Net pressure history matching for one hydraulic fracture of well D based on real-time treatment data.

Table 3.1 Calculated half-length of hydraulic fractures

Well Name	Stages	Average	Average	Total Liquid	Fracture	Half-length of Hydraulic Fracture		
		Treating	Treating	Injection	Height	Avg	Max	Min
		Time (min)	Rate (m ³ /min)	(m ³)	(m)	(m)	(m)	(m)
Well A	31	195	9.28	46641	40	127.5	166.9	82
Well B	31	176.5	9.14	44309	40	117	191.1	59.8
Well C	125	132.7	5.95	50232	40	84.1	155.7	35.6
Well D	31	140.52	9.50	38303	40	102.1	184	61.6

3.3.3 Coupled flow-geomechanics modeling

Potential activation of the faults and the trigger mechanisms of the induced seismicity can also be determined based on the Coulomb failure stress (CFS) along the fault planes (Hui et al., 2021a). The CFS criteria can be used to identify the trigger mechanisms of hydraulic fracturing-induced seismicity.

(1) Rock geomechanics

Rock mechanical properties such as Young's modulus (E) and Poisson's ratio (ν) at the well sites were calculated from well-logging data, whereas such properties between the wells were interpreted by inverting elastic modulus from the 3D seismic data. The control well E, near the study area, was logged to measure the P-wave (V_p), S-wave velocities (V_s), and density logs (ρ). The regression equations can be calculated based on the relationship between V_s and V_p , gamma-ray (GR), acoustic (AC), deep resistivity (R_t):

$$\frac{1}{V_s} = 317.8097 + 29.4894 * \frac{1}{V_p} + 11.496 * GR + 24.065 * R_t \quad (3-1)$$

$$\nu = (0.5 * \left(\frac{V_p}{V_s}\right)^2 - 1) / \left(\left(\frac{V_p}{V_s}\right)^2 - 1\right) \quad (3-2)$$

$$E = \rho V_s^2 (3V_p^2 - 4V_s^2) / (V_p^2 - V_s^2) \quad (3-3)$$

$$BI = \omega \times \frac{v_{\max} - \nu}{v_{\max} - v_{\min}} + (1 - \omega) \times \frac{E - E_{\min}}{E_{\max} - E_{\min}} \quad (3-4)$$

where V_s is the S-wave velocity, m/s; V_p is the P-wave velocity, m/s; GR is the gamma-ray, API; R_t is the deep formation resistivity, $\Omega \cdot m$; ν is the Poisson's ratio; E is Young's modulus, GPa; ρ is the density, kg/m^3 ; BI is the brittleness index; ω is the weighting factor, 0.5 in this case. The results suggested that the Poisson's ratio and Young's modulus in the study area ranged from 0.16~0.28 and 50~60 GPa, displaying a good agreement with that of 3D seismic inversion. The rock mechanics model was then developed by employing the calculated and interpreted Young's modulus and Poisson's ratio. Figure 3.6 showed the relationships between the rock geomechanics parameters and induced seismicity events frequency under different cut-off values. It showed that the events concentrated at about

50 meters above and below the treatment depth, where corresponding magnitudes of the brittleness index were relatively large. We mainly focus on the CFS Changes within the Duvernay Formation in the next coupled modeling process as the Duvernay formation shows the potential of faults reactivation.

Figure 3.6. Geomechanics parameters and statistics of induced seismicity events under different cut-off values. The events concentrated 50 meters beneath and above the treatment depth, where corresponding magnitudes of the brittleness index were relatively large.

(2) In-situ stress and pore pressure

In general, the in-situ stress regime was required to be integrated into the geomechanical model, which included the minimum horizontal stress (S_{hmin}), the maximum horizontal stress (S_{Hmax}), vertical stress (S_v), and the pore pressure (P_p). According to the previous research, the Duvernay formation near the Fox Creek region has

horizontal stress gradients ranging from 19~22.4 kPa/m for S_{hmin} and 27.1~31.7 kPa/m for S_{Hmax} . The vertical stress S_v , derived from the density log of control well E, is approximately 24.6 kPa/m, and pore pressure P_p ranges from 15.8~18.1 kPa/m. Given that the true depth of Duvernay formation in the study area is around 3,400 m, we can calculate the stress and pore pressure values. In this case, the average value of S_{hmin} , S_{Hmax} , S_v , and P_p as 70.4, 99.9, 83.8, and 57.6 MPa were adopted, respectively. The direction of S_{Hmax} is along NE45° (Reiter et al., 2014). Finally, a 3D geomechanical model incorporating the elastic modulus and stress field was built via the finite element method.

(3) Mohr-Coulomb failure criteria

Normally, a slip will be initiated along the fault plane when the stress exceeds a fault's failure strength. The Mohr-Coulomb failure criteria are the most commonly used one to characterize the reactivation of faults, which is also an efficient tool to forecast the aftershock distribution following large seismicity events (King and Deves, 2015; Catalli, 2013). The Coulomb Failure Stress is defined as:

$$CFS = \tau + \mu(\sigma_n + p_p) \quad (3-5)$$

where CFS is the Coulomb failure stress, MPa; τ is the shear stress (positive in the slipping direction), MPa; σ_n is the normal stress (positive in the extensional direction), MPa; P_p is the pore pressure (pressure of fluid filling rock pores), MPa; μ is friction coefficient. In a 2D case, if the faults' failure plane is orientated at an angle β with respect to σ_1 , the maximum principal stress, the normal stress σ_n , and shear stress τ can be given by:

$$\sigma_n = \frac{1}{2}(\sigma_1 + \sigma_3) - \frac{1}{2}(\sigma_1 - \sigma_3)\cos(2\beta) \quad (3-6)$$

$$\tau^l = \frac{1}{2}(\sigma_1 - \sigma_3)\sin(2\beta) \quad (3-7)$$

$$\tau^r = -\frac{1}{2}(\sigma_1 - \sigma_3)\sin(2\beta) \quad (3-8)$$

where σ_1 and σ_3 are the maximum and minimum principal stress, MPa; τ^l and τ^r are the shear stress in the left-lateral and right-lateral motion of the fault, MPa. The σ_1 and σ_3 were employed as 70.4 and 99.9 MPa, whereas the β was the angle between the orientation of the fault and S_{Hmax} . It is also worth noting that the equations (3-6)-(3-8) are only valid when the fault strikes parallel to the intermediate principal stress (σ_2). If not, the effect of σ_2 should be considered when estimating the normal and shear stress (Fan et al., 2016).

When a fault slips, the rocks surrounding the fault will deform elastically, and the stress field will be rearranged, leading to either a positive or negative change of CFS around the fault. In areas of positive changes of CFS, the fault will move towards a less stable state, hence increasing the subsequent slippage on nearby faults (Stiros and Kontogianni, 2009). The changes of CFS can be given by:

$$\Delta CFS = \Delta\tau + \mu(\Delta\sigma_n + \Delta p_p) \quad (3-9)$$

where Δ denotes the changes of parameters; the friction coefficient μ was determined as the value of 0.65 under the assumption of a critically stressed state.

Equation (3-4)-(3-8) were used to compute the changes of CFS on the faults during HF operations. Normally, the fault will be activated when the changes of CFS reach 0.05 MPa (King and Deves, 2015). This CFS criterion was applied in the case study to determine the activation of the inferred faults. Additionally, the Mohr circle can be plotted to illustrate the stress state of faults related to the seven clusters prior to fracturing operations, as shown in Figure 3.7. An estimated increase in pore pressure of 1.0 ~ 8.6 MPa would be required

to activate slip on these faults for Cluster 1-7 if the magnitudes of stress changes due to hydraulic fracturing operations were negligible compared to that of pore pressure increase (Figure 3.7).

Figure 3.7. Mohr circle plots for effective stress on the faults in the study area. Mohr diagram plotted using the calculated effective stresses prior to pore-pressure increase from hydraulic fracturing. The contours (units of MPa) within the Mohr circle indicated the calculated increase in pore pressure required to reactivate the faults if the stress changes were negligible.

(4) Coupled flow-geomechanics modeling

The theory of linear poroelasticity can be used to compute the stress perturbations and pore pressure changes due to hydraulic fracturing in this case (Biot, 1941). Two governing equations of linear poroelasticity can be expressed as (Kuempel, 1991; Wang and Kumpel, 2003):

$$G\nabla^2\vec{u} + \frac{G}{1-2\nu}\nabla\epsilon - \alpha\nabla p = \vec{f}(\vec{x}, t) \quad (3-10)$$

$$\frac{1}{M} \frac{\partial p}{\partial t} + \alpha \frac{\partial \epsilon}{\partial t} - \nabla \cdot \left(\frac{k}{\eta} \nabla p \right) = q(\vec{x}, t) \quad (3-11)$$

where G is the shear modulus, MPa; u is the displacement vector; ν is Poisson's ratio; ϵ is the volumetric strain; α is the Biot coefficient; $\vec{f}(\vec{x}, t)$ is the body force per unit volume on the solid matrix; M is the Biot modulus, MPa; p is the excess pore pressure, MPa; k is the permeability of the domain material, μm^2 ; η is the dynamic viscosity of the fluid, Pa.s; $q(\vec{x}, t)$ is the fluid volume injection rate (fluid source density), 1/s.

Both the body force and fluid source density functions evolve with the location and time. The equations can be solved by using the COMSOL Multiphysics software, which adapted the finite element method (FEM) using triangular elements to model the changes of poroelastic stress and pore pressure during HF operations (COMSOL Multiphysics, 2019). The geometry of the coupled model was set with the dimension $3,000 \text{ m} \times 3,500 \text{ m} \times 850 \text{ m}$. The multi-layer system was established with the thickness of the Wabamun, Gramminia, Nisku, Ireton, Duvernay, Swan Hills as 200, 50, 170, 180, 40, 210 m, respectively, based on the logging data-derived well tops. The four horizontal wells are oriented north-south with a true depth of 2,500 m. The distribution of inferred faults and hydraulic fractures was integrated into the coupled model. The fault dip angle was $\theta=85^\circ$. The hydraulic fractures of four wells were propagated following the direction of $NE45^\circ$. Rock matrix permeability was set with 394 nD (nano-Darcy) (Dunn et al., 2012), in contrast with the fracture permeability of 100 D (Darcy). We created a finite element mesh with a triangular element that honored the structure and stratigraphy of the faulted reservoir. The finite element mesh was processed to compute the element volumes and geometric transmissibility.

The boundary and initial conditions were also provided. A fixed boundary was adopted in the model where the displacement at the lateral boundaries and bottom surface was set to be zero while the top surface was in a traction-free state (Fan et al., 2019). A zero-flow rate was set to the boundaries of the model. The fluid is free to move within the whole volume. The initial fluid system in the model was under hydrostatic equilibrium. The changes of the pore pressure and stress are presented in the simulation, where $\Delta p(t=0)=0$ and $\Delta \sigma(t=0)=0$. The fracturing fluids were injected into each fracturing stage of four horizontal wells over time as injection sources in the coupled simulation. The injection rate for each stage of well A, B, C, and D was set at 9.58, 9.14, 5.95, and 9.5 m³/min, respectively (as shown in Table 3.1). The physics-controlled mesh was applied to the coupled model, with a refined mesh surrounding and in the hydraulic fractures, natural fractures and faults zone. The geological and geomechanics parameters in the model are given in Table 3.2. The well location, hydraulic fractures, inferred faults and fractures are shown in Figure 3.8.

Table 3.2 Geological and geomechanical parameters used in the coupled simulation

Property	Symbol	Value	Unit	Property	Symbol	Value	Unit
Density (Rock)	ρ	2560	Kg/m ³	Permeability (Matrix)	k	3.94E-19	m ²
Density (Fluid)	ρ_f	1000	Kg/m ³	Permeability (Fault)	k_{fault}	1.00E-20	m ²
Poisson's ratio	ν	0.25		Permeability (Fractures)	k_f	1.00E-10	m ²
Young's Modulus	E	55	Gpa	Fracture width	d_f	1.00E-03	m
Dynamic viscosity	η	0.0004	Pa.s	Maximum principal stress	$S_{H\text{max}}$	99.9	MPa
Fluid Compressibility	β	4.60E-10	/Pa	Minimum principal stress	$S_{h\text{min}}$	70.4	MPa
Biot coefficient	α	0.8		Vertical stress	S_v	83.8	MPa
Porosity	Φ	0.066		Initial pore pressure	P_p	57.6	MPa

Figure 3.8. 3D view of the coupled model used for numerical simulation. The block model contains six layers. The blue zone showed the Duvernay Formation in the model. The wells, hydraulic fractures, inferred fractures and faults were all embedded in the model.

3.3.4 Trigger mechanisms of induced seismicity

The pore pressure changes and stress perturbation during the HF operations of four horizontal wells were calculated via the newly generated flow-geomechanics model. The Mohr-Coulomb failure criterion was then employed to determine whether a fault was activated or not along with the hydraulic fracturing process. Results showed that there were three types of triggering mechanisms for HF-induced seismicity in the study area.

(1) Hydraulic fractures propagation directly triggered low-magnitude clusters.

It can be seen from Figure 3.9a that clusters 1, 3, 7, and the early part of cluster 2 were directly triggered by the HF operations as the hydraulic fractures propagated along with the orientation of S_{Hmax} . This was consistent with the aforementioned values of a low M_w and a high b . More specifically, cluster 3 was activated due to the 30-47th and 48-60th stage fracturing operation of Well C. The change of P_p was calculated to be 3 MPa, and the Δ CFS was 0.8 MPa exceeding the critical value of 0.05 MPa (Figure 3.9a-9b).

(2) Connection between hydraulic fractures and fault triggered large events

As the HF operations continued, cluster 4 and cluster 5 were activated simultaneously. Cluster 4 generated a north-south lineament located 600m west of well C and 200 m west of well D, which matched with the spatial distribution of the west fault (Figure 3.4a). The 64th to 87th fracture stages of well C connected the inferred natural fractures and reactivated the west fault. The change of P_p and Δ CFS was 3.5 MPa and 1 MPa, which also exceeded the critical value of 0.05 MPa (Figure 3.9c-9d). Cluster 5 was similar to cluster 4 but with a short lineament. In this case, the b value for cluster 5 was 0.73. The fault related to cluster 5 was activated due to the connection between the hydraulic fractures of well C (88th to 97th stage) and the fault. The change of P_p and Δ CFS was 4 MPa and 1.2 MPa. In this case, fracturing fluid has been directly injected into the faults, and the pressure diffuses rapidly through the faults and fractures. That's why cluster 4, which is located far away from the horizontal wellbore, had a quick response for the induced seismicity events.

(3) Activated natural fractures around fault triggered medium events

After the completion of well C HF operations, the zipper-fracturing pattern operations were performed on the remaining three horizontal wells. During the 9-11th stage fracturing operations of well A, cluster 6 was activated in lineament distribution at an offset of over 1.0 km away from well A. These events were characterized by medium moment magnitude, usually $0.5 < M_w < 2.5$. The b value for cluster 6 was 1.13, suggesting the reactivation of natural faults. However, the east fault was not activated due to its less favorable direction. Instead, the small-scale natural fractures around the east fault were activated due to the connection between the hydraulic fractures of Well A propagated along with NE orientation and these natural ones. The change of P_p and Δ CFS was 3.5 MPa and 1 MPa, which exceeded the critical value of 0.05 MPa and activated cluster 6 (Figure 3. 9e-9f).

Figure 3.9. Changes of Pore pressure and CFS during hydraulic fracturing of horizontal wells. (a-b) ΔP_p and ΔCFS during the 60th stage HF operation of the Well C. (c-d) ΔP_p and ΔCFS during the 97th stage HF operation of the Well C. (e-f) ΔP_p and ΔCFS during the 11th stage HF operation of the Well A. The hydraulic fractures of well C were diluted to better display in the model.

3.4 Discussion

3.4.1 Uncertainty analysis

The focal mechanism based on the regional seismological network exhibited relatively small misfits, leading to the uncertainty of event epicenters' location. Eaton et al. (2018) suggested that the location process in terms of moment-tensor solutions yields an

uncertainty of less than 30 m for the event epicenters location and 70 m for focal depths. Errors in epicenters' location posed a negative effect on the results of focal mechanism inversion, such as variations of 2% for the three components and 1° for the P and T axes orientations of the best DC source mechanisms (Zhang et al., 2019). The natural fault location derived from the focal mechanism could be calibrated further by the ant tracking results. However, it was noteworthy that noise, data artifacts, and non-fault-related lithology changes can resemble fault structure in the process of ant tracking, which means that the errors of natural fault distribution cannot be eliminated. The relatively reliable location of the inferred natural fault should be obtained based on the comprehensive analysis of event epicenters, ant tracking results, and focal mechanism of events.

In the case study, the damage zone of natural faults was ignored to simplify the coupled flow-geomechanical modeling process. The modeled faults were sealing faults with low permeability based on previous research (Zhao, 2018). The permeability of the fault was set as $1 \times 10^{-20} \text{ m}^2$ in this study, as shown in Table 3.2. Enhancement on the pore pressure has been limited to the vicinity of the injection points rather than migrating to the bottom formation layers (e.g., the basement), owing to the strike-slip fault stressing regime ($S_{Hmax} > S_v > S_{hmin}$) at the sealing faults. The result was in good agreement with the relationships between the fault permeability structure, faulting stress regime and nucleation position relative to the injection layer (Fan et al. 2019). The effect of a high-permeability damage zone on fault reactivation will be further investigated in future studies.

The S_{Hmax} orientation of NE45° was adopted. However, remarkable stress variation can be found near the study area (Fox Creek), with the orientation ranging from 44° to 64°. Moreover, the Fox Creek region is close to the Bigstone Leduc reef margin, which also

leads to the variations of S_{Hmax} . According to the rock densities from the surface to Duvernay formation in the study area and assumed up to 1% uncertainty, the vertical stress S_v was estimated to be 83.8 ± 0.8 MPa. Based on the diagnostic fracture injection tests, the minimum principal stress S_{hmin} was 70.4 ± 2 MPa in the Duvernay formation near Fox Creek. The magnitude of the maximum principal stress S_{Hmax} was estimated to be 99.9 MPa, with an uncertainty of -5.8 ± 7.3 MPa. The pore pressure at the Duvernay formation in the study area was computed to be 57.6 MPa from the pressure gradient of 17.7 kPa/m. The two additional Mohr circles were plotted under the minimum and maximum magnitude of stress state, as shown in Figure 3.10. The results demonstrated that the required increase of pore pressure activates slip on these faults for Cluster 1-7 was nearly the same. Therefore, the uncertainties of stress magnitude were negligible in this case.

Figure 3.10. Mohr circles plotted under (a) the minimum and (b) the maximum magnitude of in-situ stress and pressure.

3.4.2 Mitigation strategy of the aftershock events

The CFS changes around a fault can be simulated to predict the aftershock events. Figure 3.11a showed the CFS changes after the early part of Cluster 4 events. A positive CFS changes region was formed northward of early Cluster 4, where the maximum CFS changes reached 0.03 Mpa. Although no aftershocks were detected while fracturing Well C, the afterward fracturing operations on well D further increased the CFS change to 1.5 MPa, which activated the later part of cluster 4. Figure 3.11b and 11c illustrated that all the aftershock events were located in the positive CFS changes region. The trigger mechanism of such aftershocks was the direct connection between hydraulic fractures and pre-existing fault.

Thus, the operational parameters of well D, such as the injection rate and volume, need to be reduced to mitigate the aftershocks risks. For example, we could reduce the injection rate from 9.50 m³/min to 3.0 m³/min, based on the distance between the well D and the west fault. Accordingly, the average half-length of 11-16th stage hydraulic

fractures of well D will decrease to 50.1 m from the previous 102.8 m. Under this scenario, the CFS changes around the west fault would be zero owing to no direct connection between faults and hydraulic fractures. Additionally, the maximum CFS changes due to early cluster 4 were 0.03 MPa, which was less than the critical value of 0.05 MPa. Hence no aftershock events would occur in this case, shown in Figure 3.11d.

Figure 3.11. Aftershock analysis after Cluster 4 and mitigation strategy. (a) CFS changes after the early part of Cluster 4 events. The red line denoted the Fault 1 distribution in the Duvernay Formation, whereas the

green line represented its distribution in the upper Iron Formation. (b) Aftershock events during well D 11-16th stage operations. All aftershock events were located in the positive CFS changes region. (c) CFS changes due to well D 11-16th stage operations. The maximum magnitude of CFS changes was 1.5 MPa and activated the later part of cluster 4. (d) CFS changes after reducing injection pressure of well D. The average half-length of 11-16th stage hydraulic fractures of well D was reduced to 90 m, and no aftershock events occurred in this case.

3.5. Summary

An integrated approach of the geological, geophysical, and flow-geomechanics analysis was proposed, and the linkages among the regional faults, induced seismicity sequence, and reservoir hydraulic fracturing operations were established in this study. The following conclusions are drawn from the case study.

- (1) The proposed integrated approach can identify the trigger mechanisms of hydraulic fracturing-induced seismicity in tight and shale reservoirs. Three types of triggering mechanisms were accounted for HF-induced seismicity, including hydraulic fractures propagation, the connection between hydraulic fractures, and a fault and connections of hydraulic fractures with the natural fractures around the fault. The larger moment magnitude events were usually triggered by reactivation of faults, whereas the smaller ones were induced by hydraulic fractures propagation.
- (2) The flow-geomechanics model was used to compute the CFS changes and determine the reactivation of faults. The calculated results were in good agreement with the monitored induced seismicity, both spatially and temporally.
- (3) In the ToC2ME case, the cluster 1, 3, 7 and the beginning part of cluster 2 were associated with the propagation of hydraulic fractures whereas clusters 4, 5, 6 and

subsequent part of cluster 2 were linked to the reactivation of natural faults and fractures.

- (4) The injection rate could be decreased to mitigate the risks of aftershocks for the ToC2ME field case. The half-length of hydraulic fractures will be reduced accordingly, and there will be no direct connection between faults and hydraulic fractures.

CHAPTER 4 INVESTIGATION ON TWO MW 3.6 AND MW 4.1 EARTHQUAKES TRIGGERED BY POROELASTIC EFFECTS OF HYDRAULIC FRACTURING OPERATIONS²

Abstract

A coupled approach of fluid flow and geomechanics is proposed in this paper to quantitatively understand the hydraulic fracturing-induced poroelastic effects that activate pre-existing faults and trigger earthquake swarms near Crooked Lake, Alberta. The 3D poroelastic simulation of the seismogenic fault zone is then conducted to characterize the pressure diffusion and stress perturbation that led to fault activation. Results show that the poroelastic effects on the high-permeable damage zones of a conductive-barrier fault triggered the sequential activation of the seismogenic fault in the basement and Winterburn Formation. In addition, the high-permeable damage zones act as conduits for pore pressure diffusion along the fault, whereas the fault core functions as a barrier to prevent crossing flow. The poroelastic effects in terms of pressure diffusion and stress perturbation in response to fluid injection facilitated the fault slip and hence triggered the Mw 3.6 earthquake in the basement formation forty days after the fracturing operations. Moreover, the mainshock created negative Coulomb failure stress changes, inhibiting further fault slip in the basement formation. Subsequently, the stimulation of another well facilitated poroelastic effects on the fault damage zone in top Winterburn formation, reactivating the same fault with an Mw 4.1 earthquake eight days after the initiation of treatments. It is essential to optimize the injection site selection near the existing faults to reduce the risks of the induced seismicity near Crooked Lake.

² Hui, G., Chen, S., Chen, Z., et al. (2021a). Investigation on Two Mw 3.6 and Mw 4.1 Earthquakes Triggered by Poroelastic Effects of Hydraulic Fracturing Operations near Crooked Lake, Alberta. *Journal of Geophysical Research: Solid Earth*. 126, e2020JB020308. <https://doi.org/10.1029/2020JB020308>

4.1 Introduction

Recent evidence suggests that the increasing earthquakes in North America have been ascribed to industrial activities for resource development, including wastewater disposal, fluid production, geothermal systems, and hydraulic fracturing operations (Atkinson et al., 2016). It is believed that many induced seismicity events with the moment magnitude of M_w larger than 3 in Western Canada are spatiotemporally related to the hydraulic fracturing (HF) activities in the area. For example, an M_w 4.1 earthquake, occurred on 12 January 2016 near Crooked Lake, Alberta, and a local magnitude M_L 4.18 earthquake, reported on 29 March 2019 near Red Deer, Alberta, are both attributed to HF operations (Eyre et al. 2019; Schultz et al., 2020). The HF has been demonstrated to be a practical and effective technique to develop unconventional reservoirs in Western Canada. During HF treatments, the pressurized fracturing fluids are first pumped into the target formation to cause the tensile failure of rocks. The selected proppants (e.g., sands) are then injected into newly generated fractures to keep them open during the subsequent hydrocarbons production. Hence a pathway for fluid flow was established with a high permeability between wellbores and the target reservoir. In general, the stimulation process is accompanied by microseismic events with low magnitudes. However, large earthquakes may be nucleated once there are direct hydraulic connections between the stimulated wells and pre-existing faults during HF stimulation (Schultz et al., 2015; Schultz et al., 2017; Eaton and Schultz, 2018).

The fundamental mechanisms of HF-induced seismicity include: (1) the direct pressure communication between the stimulated wells and the seismogenic fault; and (2) the poroelastic stress transfer from the stimulated reservoir to the nucleated formation

(Ellsworth, 2013). In both scenarios, the seismic slip will be initiated along the fault plane when the poroelastic stress exceeds the failure strength of the fault (Healy et al., 1968; King and Deves, 2015). It is worth noting that the nucleation position and time of HF-induced seismicity exhibit a high degree of variety in Western Canada (Eaton et al., 2018). For example, the M_w 3.2 earthquake swarm in November 2016 primarily clustered within the stimulated formation during fracturing completions. The cause of the earthquake was owing to the hydraulic connection between the inferred faults and stimulated wells (Eaton et al., 2018; Zhang et al., 2019; Igonin et al., 2019; Hui et al., 2021a, 2021b). Alternatively, the M_w 3.6 earthquake occurred twenty days after the operation ended (Schultz et al., 2015; Bao and Eaton, 2016; Wang et al., 2017). The time lag of this recorded earthquake was attributed to the elevated pore pressure and stress perturbation on the adjacent faults (Bao and Eaton, 2016). Moreover, the M_w 4.1 clusters were monitored in January 2016 in the top Winterburn Formation right after treatments ended, which was induced by the enhancement in pore pressure (Schultz et al., 2017; Wang et al., 2018; Eyre et al., 2019). Interestingly, the M_w 3.6 and M_w 4.1 earthquake swarms were ascribed to the sequential reactivation of the same basement-rooted fault (Chopra et al., 2017; Eyre et al., 2019). However, the underlying mechanism is still uncertain that causes the same fault to slip sequentially over the span of thousands of meters vertically due to fracturing operations.

In this study, a coupled approach of fluid flow-geomechanics is proposed to quantitatively characterize the poroelastic effects on the basement-rooted fault due to HF operations near Crooked Lake. 3D poroelastic simulation of the seismogenic fault zone is conducted to quantify the conditions under which the fault is sequentially reactivated in the basement and top Winterburn Formation. The sensitivity analysis for operational

parameters is performed to propose mitigation strategies to reduce the risks of potential seismic hazards.

4.2 Field Background

The Fox Creek region has witnessed a notable increase in induced seismicity due to hydraulic fracturing since 2013 (Schultz et al., 2017; Pawley et al., 2018). These HF-induced seismicity events have been primarily related to geological susceptibility, including the overpressure features of Duvernay formation (Eaton and Schultz, 2018), proximity to reef edges in Swan Hills formation (Schultz et al., 2016), critically stressed state of faults (Zhang et al., 2019) and proximity to the Precambrian basement (Pawley et al., 2018). Moreover, operational parameters (i.e., pumped fluid volume, rate, and pressure) also play a significant role in HF-induced seismicity (Schultz et al., 2018). Since June 2010, as many as 579 horizontal wells have been hydraulically stimulated to develop unconventional resources in the Duvernay formation near Fox Creek (dataset ended in November 2018). It is shown that the average injection volume of fluids reached as many as 39732 m³ per well statistically, making the fracturing operations appear to induce potential earthquakes (McGarr, 2014). Consequently, the geological susceptibility and operational parameters were both crucial factors that influenced the HF-induced seismicity in Fox Creek.

Two earthquake swarms investigated in this study are located in the west of the Fox Creek region. The north M_w 3.6 swarms are first scrutinized by comparing the spatiotemporal correlations between earthquake swarms and stage completions. From 17 December 2014 to 9 January 2015, the zipper-pattern treatments (alternated stage completions) were performed southward on two horizontal wells, well A and well B

(Figure 4.1a). A period of temporary seismic quiescence was observed in the first 20 days of stage completions (Figure 4.1c). Then the east cluster (blue balls in Figure 4.1a) was suddenly activated at an offset of approximately 770 m from well B. This cluster exhibited a roughly N-S-trending lineament with a magnitude ranging from 0.5 to 3.0 (Figure 4.1a). Several days later, the mid-east cluster (light blue balls) with a magnitude range of 0.47~2.4 occurred at a relatively shorter offset from well B. The activation of both clusters continued for up to 6 days until 11 January. Then, a temporary dormant period was observed again until the sequential nucleation of three moderate earthquakes, the M_w 2.6, M_w 3.6, and M_w 3.0 events (light green balls), displaying an approximately N-S-trending lineament approaching well B. Afterward, the intermittent activation of other events lasted until 31 March with magnitudes less than 2 (green balls). Based on the focal mechanism inversions, the hypocenters of these earthquakes are located 300 m ~ 700 m beneath the stimulated site (Figure 4.1b). The lineament distribution and basal nucleation for these clusters indicate the potential activation of a basement-rooted fault with an N-S-trending strike. Moreover, the injection rate and pressure are counted to be 9.5 m³/min and 70 MPa per stage of both wells. The cumulative injection volume is 61,149 m³, and the total volume of flowback fluids is 4,277 m³ (Bao and Eaton, 2016), suggesting that a maximum volume of 56,872 m³ fluids are injected into the associated formations and faults.

In January 2016, another south well, well C, was hydraulically stimulated from the same well pad and was associated with the south swarm (Figure 4.1a). As many as 9769 events with a maximum magnitude of 4.1 were detected by the seismological networks (Eyre et al., 2019). The hypocenters of these earthquakes are approximately 150 m ~ 400 m above the stimulated Duvernay formation (Figure 4.1b). In this study, only fifteen events

associated with the M_w 4.1 earthquake are investigated, as shown in Figure 4.1. Specifically, no seismic events were activated during the first 24 stage completions. However, on 12 January, a red-light event of M_w 4.1 nucleated at an offset of 160 m from well C, causing the cessation of treatments (Figure 4.1c). Only 26 out of 30 planned stage completions were accomplished. Despite the shutdown of operations, some low-magnitude events were still activated with an N-S trending lineament (Figure 4.1a), which was regarded as the aftershocks of the M_w 4.1 event. Based on the statistics of treatment parameters, well C is stimulated with an average injection rate of $8.36 \text{ m}^3/\text{min}$ and pressure of 70 MPa per stage. Given no available flowback data, we compare the total volume of Well C with that of Well B and assume the same ratio of flowback fluids to total fluids. Therefore, an estimated volume of $29,046 \text{ m}^3$ out of $31,230 \text{ m}^3$ in Well C is assumed to be pumped into corresponding faults and formations.

The comparison of the spatial features of M_w 3.6 and M_w 4.1 earthquake swarms shows that both swarms displayed the same N-S lineaments at the analogous offsets from well C (Figure 4.1a). The focal mechanisms of both swarms also exhibited a high degree of similarity. Moreover, the b value for both swarms was estimated to be 0.85 and 0.86, respectively, indicating the possible existence of the same seismogenic fault. This speculation was validated by the following fault interpretation from a 3D reflection seismic survey.

Figure 4.1. (a) Locations of two earthquake swarms (solid balls) detected by the seismology stations near Crooked Lake, west of Fox Creek, Alberta. The circles are scaled by the magnitude and colored by time. Two beach balls show the corresponding focal mechanisms (Wang et al., 2017). Also shown were three horizontal wells (orange, blue, and pink lines). The red dashed line represents the possible seismogenic fault. The inset map shows the location of the studied region. (b) Cross-sectional views of induced seismicity and horizontal wells. The profile lines A-A' and B-B' are shown in (a). (c) Time sequence showing induced seismicity and hydraulic fracturing treatment data for three horizontal wells. The solid line denotes the cumulative injection volume. The colored cycles represent the monitored events. The dashed black lines mark a specific time after the onset of fracturing operations.

4.3 Methods

In this study, a coupled approach of fluid flow and rock geomechanics is proposed to elucidate the underlying mechanisms of two earthquake swarms. First, the basement-rooted faults in the vicinity of horizontal wells are identified from the 3D reflection seismic survey. Next, the related properties of these faults are investigated, including the faulting stress regime, mechanical properties, and fault architecture. Last, the coupled flow-geomechanics simulation is conducted to quantify the poroelastic effects that activated the faults and triggered the earthquake swarms.

4.3.1 Seismogenic Faults Identification and Hydraulic Fractures Propagation

Fault Interpretation. The availability of the reflection 3D seismic data provides insights to explore the possible linkage between induced seismicity and structural features. Specifically, the synthetic-seismogram-tie for key wells is first established that can pick the related horizons in the reflection survey. The associated faults are then identified by tracing structural discontinuities or offsets in the time-domain reflection profile. After accomplishing the time-depth conversion via a 3D velocity model, the faults are finally contoured in the depth domain. The interpretation results could be further validated by the focal mechanism of related clusters.

Hydraulic Fractures Propagation. During HF operations, hydraulic fractures generally propagate parallel to the orientation of S_{Hmax} . The Perkins-Kern-Nordgren (PKN) model is employed in this study to estimate the geometry of hydraulic fractures (Yew and Weng, 1997). In the PKN model, the fracture height is fixed to be the thickness of stimulated formation. The cross-sections of hydraulic fractures tend to be elliptical. In this work, the

leak-off effect is not considered due to the low matrix permeability of shale reservoirs. Then the fracture half-length $L(t)$, width $W(t)$, and wellbore pressure $P_w(t)$ for a single stage at a given time was calculated by:

$$L(t) = 0.68 \left[\frac{Gq_0^3}{(1-PR)\mu h^4} \right]^{1/5} t^{4/5}, \quad (4-1)$$

$$W(t) = 2.5 \left[\frac{(1-PR)\mu q_0^2}{Gh} \right]^{1/5} t^{1/5}, \quad (4-2)$$

$$P_w(t) = 2.5 \left[\frac{G^6 \mu q_0^2}{(1-PR)^4 h^6} \right]^{1/5} t^{1/5}, \quad (4-3)$$

where G is shear modulus, MPa; q_0 is pumped fluid rate, m^3/s ; PR is Poisson's ratio; μ is the viscosity of the pumped fluid, $Pa \cdot s$; h is fracture height, m ; and t is the given time, s . The shear modulus G was derived from Poisson's ratio PR and Young's modulus YM using the expression $G = YM/2/(1+PR)$.

4.3.2 Stress field, mechanical properties, and fault architecture

In-situ Stress Field. The local stress field imposes a significant effect on the nucleation position of induced seismicity during fracturing operations. The seismogenic faults in previous works in Fox Creek have been corroborated to display the strike-slip motions (Reiter and Heidbach, 2014; Schultz et al., 2017; Eaton et al., 2018; Shen et al., 2019). Under the strike-slip stress field, conductive faults are usually activated in the formations below or above the stimulated formation rather than within the stimulated layer (Fan et al., 2019). Normally, the type of stress field was determined by comparing the magnitudes of three principal stresses, including the maximum principal stress (S_{Hmax}), the minimum principal stress (S_{hmin}), and the vertical stress (S_v). The strike-slip, normal, and reverse

faulting stress regimes are uniquely discerned by $S_{Hmax} \geq S_v \geq S_{Hmin}$, $S_v \geq S_{Hmax} \geq S_{Hmin}$, $S_{Hmax} \geq S_{Hmin} \geq S_v$, respectively (Zoback, 2007).

Rock Mechanical Properties. The robust estimation of mechanical properties (i.e., Young's modulus and Poisson's ratio) could better evaluate the poroelastic effects on related faults during HF stimulation. Generally, the dynamic elastic parameters are derived from velocity logging data of nearby wells and then calibrated by the static parameters measured in the triaxial compressive experiments. The brittleness index (BI) is introduced as an indicator to assess the brittleness of rocks (Ronald et al., 2019), which might account for the geomechanical bias for fault activation in specific horizons. The related expressions are given by:

$$PR_{dyn} = (0.5 * (V_p/V_s)^2 - 1) / ((V_p/V_s)^2 - 1) \quad (4-4)$$

$$YM_{dyn} = \rho V_s^2 (3V_p^2 - 4V_s^2) / (V_p^2 - V_s^2) \quad (4-5)$$

$$BI = \omega \times \frac{PR_{sta_max} - PR_{sta_min}}{PR_{sta_max} - PR_{sta_min}} + (1 - \omega) \times \frac{YM_{sta_max} - YM_{sta_min}}{YM_{sta_max} - YM_{sta_min}} \quad (4-6)$$

where V_s is the velocity of S-wave, m/s; V_p is the velocity of P-wave, m/s; PR_{dyn} and PR_{sta} are the dynamic and static Poisson's ratio, respectively; YM_{dyn} and YM_{sta} are the dynamic and static Young's modulus, respectively, GPa; ~min and ~max are the associated minimum and maximum measured value, respectively; ρ is density, kg/m³; BI is brittleness index, and ω is the weighting factor.

Moreover, the percentages of total organic content (TOC) and clay content (V_{clay}) are also a significant indication for the assessment of fault stability (Eyre et al., 2019). Based on logging data of spectral gamma-ray, TOC and V_{clay} could be estimated from the uranium and thorium content, respectively, in the associated formations (Doveton, 1994).

Fault Zone Architecture.

A typical fault zone contains a low-permeability fault core bounded by highly-fractured damage zones with a relatively high permeability (Chester et al., 1993; Yehya et al., 2018). During HF operations, the role of a fault as an impermeable barrier, a flow-conduit, or a combination of both depends on stratigraphic juxtaposition, fault zone architecture, and permeability attributes for two components (Caine et al., 1996; Fan et al., 2016). Besides, mechanical shearing during fault slip may alter the porosity and permeability of the fault zone. In this work, an empirical model was utilized to characterize the effect of poroelastic deformation on the porosity and permeability (Yehya et al., 2018), using the following expressions:

$$\phi = 1 - (1 - \phi_0)e^{-\epsilon}, \quad (4-7)$$

$$k = k_0 (\phi / \phi_0)^n, \quad (4-8)$$

where ϕ and ϕ_0 are deformation-dependent porosity and initial porosity; ϵ is the volumetric strain; k and k_0 are deformation-dependent permeability and initial permeability, and n is the exponent coefficient.

Based on the comprehensive analysis of the in-situ stress field and fault zone architecture, a preliminary schematic pattern is proposed in Figure 4.2. This pattern shows the conditions under which a single basement-rooted fault is reactivated sequentially in the basement and top Winterburn Formation due to the HF stimulation. The pattern would be further validated via the following poroelastic simulation.

Figure 4.2. A schematic diagram of fault activation due to HF stimulations. The fault is enlarged in scale to better display its conduit-barrier features. The gray subvertical layer denotes the low-permeability fault core bounded by two highly-fractured high-permeability damage zones. The Duvernay formation is shown as the thin green layer, in which three multistage horizontal wells are stimulated. The purple layer denotes formations above the Duvernay formation, and the brown layer represents formations below it.

4.3.3 Coupled fluid flow-geomechanics modeling and fault reactivation criterion

The theory of linear poroelasticity is adopted in this work to quantify the physical process of fluid diffusion and elastic deformations (Biot, 1941; Wang, 2000). Specifically, the fluid flow through a porous medium is described in previous works using the following continuity equation:

$$\frac{\partial}{\partial t}(\rho\phi) + \nabla \cdot (p\vec{q}) = Q_m \quad (4-9)$$

where ρ is the density, kg/m³; ϕ is the porosity; $\nabla \cdot$ is divergence; $\vec{q}$ is the flow rate, m³/s; Q_m is the fluid mass source.

Meanwhile, the solid matrix is assumed to be in an equilibrium state. Hence, the stress change after applying body force on this matrix is given by:

$$\nabla \cdot \sigma = \vec{f}(\vec{x}, t) \quad (4-10)$$

where σ is the stress tensor, $\vec{f}(\vec{x}, t)$ is the per-unit-volume body force placed on the solid matrix.

Finally, the poroelasticity process could be characterized by combining two equations to quantitatively assess the stress perturbation and pore pressure change during HF operations (Wang and Kumpel, 2003). The integrated equations are given by:

$$G\nabla^2\vec{u} + \frac{G}{1-2PR}\nabla\epsilon - \alpha\nabla P_{ep} = \vec{f}(\vec{x}, t) \quad (4-11)$$

$$\frac{1}{M}\frac{\partial P_{ep}}{\partial t} + \alpha\frac{\partial\epsilon}{\partial t} - \nabla \cdot \left(\frac{k}{\mu}\nabla P_{ep}\right) = q(\vec{x}, t) \quad (4-12)$$

where G is shear modulus, MPa; u is displacement vector; PR is Poisson's Ratio; ϵ is volumetric strain; α is Biot's coefficient; P_{ep} is excess pore pressure, MPa; M is the Biot modulus; k is the permeability of the domain material, m²; μ is the dynamic viscosity of the fluid, Pa·s, and $q(x,t)$ is the volume injection source rate, 1/s.

After characterizing the changes of pore pressure and in-situ stress surrounding the fault zone, the Mohr-Coulomb criterion is then adopted to determine the activation of related faults (Catalli et al., 2013), using the following equation:

$$\Delta CFS = \Delta \tau + \mu(\Delta p_{ep} + \Delta \sigma_n) \quad (4-13)$$

where Δ denotes the changes of each parameter; τ is shear stress, MPa; σ is the normal stress, MPa; p_{ep} is the pore pressure changes, MPa; and μ is the static coefficient of friction. τ is defined as positive in the slip direction and σ_n as positive in the extensional direction. μ is assumed to be 0.65 showing the critically stressed state of the fault.

The Mohr's circle is commonly utilized to characterize the stress state of the fault before and after HF operations and determine the spatiotemporal fault activation (King and Deves, 2015). The effective normal stress σ_n' , and the shear stress τ used in the 2D Mohr's circle are given by:

$$\sigma_n' = \frac{1}{2}(\sigma_1 + \sigma_3) - \frac{1}{2}(\sigma_1 - \sigma_3) \cos(2\beta) - p_{ep} \quad (4-14)$$

$$\tau^r = -\frac{1}{2}(\sigma_1 - \sigma_3) \sin(2\beta) \quad (4-15)$$

$$\tau^l = \frac{1}{2}(\sigma_1 - \sigma_3) \sin(2\beta) \quad (4-16)$$

where σ_1 and σ_3 represent the magnitude of S_{Hmax} and S_{Hmin} , MPa; τ^r and τ^l are the shear stress in the right-lateral and left-lateral motion of the fault, MPa. β is the angle between S_{Hmax} orientation and fault strike. It is worth noting that the intermediate principal stress (σ_2) should be considered in the calculation if the fault strike is not parallel to σ_2 (Fan et al., 2016).

Besides the determination of spatial fault activation, the Mohr-Coulomb criterion could also be utilized to forecast the aftershocks after a large-magnitude earthquake. Specifically, as a fault slips, the surrounding rocks will deform elastically and then

rearrange the regional stress regime. This mechanical process resulted in positive and negative ΔCFS in the vicinity of the fault. In regions of positive ΔCFS (generally larger than 0.05 MPa), the fault will enter an unstable state, increasing the potential of subsequent slippage and then triggering the aftershocks. Hence the aftershocks distribution could be forecasted by determining the regions with positive ΔCFS (King and Deves, 2015).

4.4 Results

4.4.1 Pre-existing faults identification and hydraulic fractures propagation

(1) Seismic interpretation of pre-existing faults

The reflection 3D seismic data is utilized to interpret the seismogenic faults related to earthquake swarms (Chopra et al., 2017; Eyre et al., 2019). Five inferred faults cut through the Precambrian basement upward into the top Winterburn formation, along with Fault 1 is spatially correlated with the M_w 3.6 and M_w 4.1 earthquakes (Figure 4.3a). The strike and dip of Fault 1 are $\sim 176^\circ$ and $\sim 83^\circ$, consistent with focal inversions of two swarms, as shown in Figure 4.1 (Zhang et al., 2016; Wang et al., 2017). Moreover, Fault 2 and Fault 3 also exhibit a high degree of consistency with the lineament distribution of the east and south clusters (Figure 4.3b). It is also shown that although Fault 4 and Fault 5 display the aseismic pattern during treatments, both faults possibly act as flow conduits to propagate fluid pressure into the seismogenic Fault 1 and Fault 3 (Figure 4.3b).

(2) Estimated propagation of hydraulic fractures using PKN model

Based on the stratigraphic correlation of two nearby straight wells, the thickness of the Duvernay formation is estimated to be 44.9 m. The mechanical properties are obtained from the velocity logging data listed in Table 4.1. Additionally, the real-time treatment data

of three horizontal wells are collected from the field (Bao and Eaton, 2016; Eyre et al., 2019). Then the PKN model is adopted to compute fracture half-length and width using Equations (4-1) and (4-2). Results show that well A, B, and C have an average fracture half-length of 79.6, 76.3, and 86.7 m, respectively (Figure 4.3b) and an average aperture width of 0.0252, 0.0246, 0.0253 mm, respectively. According to the tensile fracture permeability formula between fracture permeability and fracture aperture (Qu et al., 2016), the fracture permeability is estimated to be approximately $9.87 \times 10^{-14} \text{ m}^2$, in sharp comparison with the shale matrix permeability of only $4.11 \times 10^{-19} \text{ m}^2$ (from core analysis). This calculation result would be introduced into the following poroelastic simulation to describe the permeability changes surrounding horizontal wellbores. In this work, we assume one effective hydraulic fracture for each fracturing stage that has a higher permeability than the shale matrix. The permeability in the hydraulic fractures has been assigned to the constant value of approximately $9.87 \times 10^{-14} \text{ m}^2$ during the coupled simulations. The stages have been simulated with the actual injection rate following the fracturing sequence (Figure 4.1c). Figures 4.3c-3d show the 3D view of fracture and fault networks and induced events. It is found that both hydraulic fractures of Well B and Well C propagate along NE45° and are directly connected with Fault 1. The HF-fault connections would be incorporated into the following coupled model.

Figure 4.3. (a) Cross-section view of inferred faults in a 3D seismic survey. Five subvertical faults are identified (black lines). Fault 1 is spatiotemporally associated with the two earthquakes. “C” denotes the possible channel visible as a “bowtie” structure, while “SR” represents the edge of the Swan Hills reef structure (edited from Eyre et al. 2019). (b) Map view of horizontal wells, induced seismicity, and inferred faults. The background colors represent curvature attributes used for fault interpretation (Chopra et al., 2017). The blue and red stars indicated the location of two earthquakes. The red lineaments denote five inferred faults. The green line shows the profile line in the 3D seismic survey, shown in Figure 4.3a. The short lines overlying wellbores represent calculated hydraulic fractures (c-d) The 3D view of fracture and fault networks, hydraulic fractures, and induced seismicity. The magenta rectangles mark the HF-fault connection positions.

4.4.2 Investigation of in-situ stress field, mechanical properties, and fault architecture

(1) Determination of full stress tensor

Generally, the orientation of S_{Hmax} is derived from the borehole breakouts and drilling-induced tensile fractures. Reiter and Heidbach (2014) investigated the stress orientation database in Western Canada and concluded that S_{Hmax} near Fox Creek was mainly oriented $NE45^{\circ} \sim NE47^{\circ}$. Shen et al. (2019) integrated the results from the World Stress Map (Heidbach et al., 2016) using the Inverse Distance Weighting approach, demonstrating the S_{Hmax} orientation of $NE43^{\circ}$ in Fox Creek. In this paper, S_{Hmax} orientation is employed as $NE45^{\circ}$, consistent with prior studies on stress orientations near Crooked Lake (Schultz et al., 2017; Eyre et al., 2019).

The magnitude of S_v is obtained from the vertical integration of density logs, using the following equation: $S_v = \rho_{avg} * g * z$, where ρ_{avg} is the average density of overburden formation, kg/m^3 ; g is the acceleration of the gravity, m/s^2 ; and z is the measured vertical depth, m. The uncertainty of S_v is set up to 1% of the calculated magnitude, following the study of Zoback (2007). Therefore, the gradient of S_v is calculated to be 24.6 ± 0.25 kPa/m, in agreement with prior works (Zhang et al., 2019; Eyre et al., 2019).

The pore pressure P_p could be estimated from the steady pressure at the end of stage completion in the treatment data diagram (Figure 4.4a). We also used the Eaton method (Eaton, 1975) to predict pore pressure from the stress, hydrostatic pressure, and sonic log data, which is given by:

$$P_p = S_v - (S_v - P_n)(\Delta t_{norm}/\Delta t)^x \quad (4-17)$$

where P_n is hydrostatic pore pressure, MPa; Δt_{norm} is the acoustic travel time from the normal compaction trend at the given depth, μs ; Δt is the observed acoustic travel time from the sonic log, μs ; and x is an exponent index. Based on the treatment data and log

data analysis, the average reservoir depth and the estimated pore pressure for three wells reached 3387 m and 57.9 MPa, respectively. Then the gradient of P_p was estimated to be 17.1 kPa/m, consistent with the mean value of 16.8 kPa/m in the Duvernay formation (Eaton and Schultz, 2018). The overpressure feature plays an important role in HF-induced seismicity in Fox Creek.

The closure pressure that is required to hold a fracture open is utilized to compute S_{hmin} . Based on the statistics of closure pressure for three wells, the gradient of S_{hmin} is evaluated to be 20.92 ± 0.56 kPa/m that coincides with 19~22.4 kPa/m for the Kaybob Duvernay play (Eyre et al., 2019). Finally, by using the following expression: $S_{Hmax} = 3S_{hmin} - 2P_p$ (Zoback, 2007), the gradient of S_{Hmax} is estimated to be 29.16 ± 1.68 kPa/m, which agrees with prior works (Zhang et al., 2019; Eyre et al., 2019; Shen et al., 2019).

Overall, the faulting stress regime in this study is determined to be a strike-slip regime by comparing the magnitudes of three stress tensors ($S_{Hmax} \geq S_v \geq S_{hmin}$). Then the Mohr's circle for two earthquake swarms is plotted to illustrate the initial stress state of Fault 1 (Figure 4.4b). It is shown that an increase in pore pressure of at least 2.0 MPa is required to activate Fault 1 if the in-situ stress changes are negligible relative to pressure changes.

(2) Calculation of mechanical and hydraulic properties

The robust estimation of mechanical properties is required to quantify the poroelastic responses to the fault during HF operations. The logging data from a nearby well is utilized, which measures both velocities (V_p , V_s) and rock density (ρ) from the Wabamun formation to Gilwood formation. The data from the Gilwood formation to Precambrian formation are derived from the prior work (Ronald et al., 2019). Then the

dynamic elastic parameters (i.e., PR and YM) for related horizons are obtained using Equations (4) and (5). Meanwhile, the static elastic parameters are derived from the triaxial compressive experiments for three nearby wells. Consequently, the dynamic mechanical properties could be calculated based on the relationship between the static (~sta) and dynamic (~dyn) parameters, using the following equations:

$$PR_{\text{dyn}} = 0.734 * PR_{\text{sta}} + 0.0716 \quad (4-18)$$

$$YM_{\text{dyn}} = 0.564 * YM_{\text{sta}} + 19.9 \quad (4-19)$$

Next, these dynamic parameters were utilized to calculate the brittleness index BI for each horizon using Equation (6). Similarly, the TOC+clay weight percentage ($V_{\text{TOC+clay}}$) was estimated based on the regression equation between the measured $V_{\text{TOC+clay}}$ of core sample and particular logs, including the gamma-ray (GR), density (AC), and deep resistivity (Rt). The regression expression was given by:

$$V_{\text{TOC+clay}} = -0.2865 + 1.0898 * GR' - 0.3336 * DEN' + 0.7017 * RT' \quad (4-20)$$

where GR', DEN' and RT' are the normalized gamma-ray, density, and deep resistivity, respectively, calculated by $(x - x_{\text{min}}) / (x_{\text{max}} - x_{\text{min}})$. x denoted three aforementioned logging data.

Additionally, the hydraulic properties (i.e., porosity and permeability) in each formation are also determined to characterize the fluid flow behavior through a porous system. Specifically, the core analysis values for five nearby wells are first calibrated to the logging depth. The regression relationship is then established between the measured porosity and particular well logs. Finally, the porosity (ϕ) and permeability (k, nD) for all depth are calculated using the following equations:

$$\phi = 0.04336 - 0.04678 * GR' + 0.07409 * DT' - 0.06765 * DEN' + 0.01462 * RT' \quad (4-21)$$

$$k = 16.9422 * \phi^{4.1843} \quad (4-22)$$

Figure 4.4c shows the calculated dynamic mechanical, hydraulic parameters, and total TOC+clay content by depth. The induced seismicity is concentrated in the high-BI formations. Although the Duvernay formation exhibits a large BI value, the high content of TOC+clay made it keep in a stable state instead. However, in the Winterburn, Cambrian, and Precambrian basement formation, a high BI magnitude and low TOC+clay content make these formations subordinate to a less stable state. Table 4.1 shows the mechanical and hydraulic properties of each formation. The Poisson's ratio and Young's modulus have a variety of 0.19 ~ 0.31 and 48 ~ 73 GPa, respectively. The porosity and permeability have a range of 0.02 ~ 0.16 and $5.2 \times 10^{-20} \sim 1.43 \times 10^{-16} \text{ m}^2$, respectively. Based on the efficiency of pore fluid in response to applied stress, the Biot's coefficient (α) is assigned to a value of 0.44 for low permeability formations and 0.79 for high permeability formations (Fan et al., 2019).

(3) Determination of fault zone architecture

The fault architecture in this work follows the pattern shown in Figure 4.2, wherein the thickness of damage zones and fault core are assigned to 20 m and 5 m, respectively (Yehya et al., 2018). The permeability of fault core and damage zones are set with 10^{-20} m^2 and 10^{-14} m^2 , respectively, based on prior works on permeability structures of conduit-barrier faults (Yehya et al., 2018; Fan et al., 2019). The vertical mechanical properties of fault are consistent with those of corresponding formations transected by the fault. Under these constraints on the fault zone architecture, the damage zones would provide a

hydraulic conduit for pressure diffusion along faults, whereas the fault core would act as an impermeable barrier for fault-crossing flow during HF operations.

Figure 4.4. (a) Mohr's circle plots showing the initial stress state of Fault 1 in two swarms. Mohr diagram is plotted using the estimated stress tensor prior to fracturing operations. (b) Calculated mechanical, hydraulic parameters and total TOC+ clay content by depth. The number of events over depth is also shown.

Table 4.1. Hydraulic and mechanical rock properties for each horizon in the study region

Formation/Property	Thickness	PR	YM	BI	Porosity	Permeability	TOC+SH	Biot* ^d
unit	(m)		(GPa)			(m ²)		

Wabamun ^{*a}	300	0.31	61	0.45	0.15	1.38E-16	0.04	0.79
Winterbun ^{*a}	200	0.29	73	0.54	0.16	1.43E-16	0.12	0.79
Ireton ^{*a}	160	0.24	48	0.48	0.07	6.46E-18	0.35	0.44
Duvernay ^{*a}	40	0.19	50	0.61	0.065	4.11E-19	0.34	0.44
Swan Hills ^{*a}	100	0.30	70	0.47	0.05	7.10E-19	0.06	0.44
Gilwood ^{*a}	100	0.24	66	0.60	0.05	3.36E-18	0.03	0.79
Cambrian ^{*b,c}	200	0.25	66	0.60	0.02	5.20E-20	0.01	0.79
Basement ^{*b,c}	300	0.25	66	0.60	0.02	5.20E-20	0.01	0.44

^{*a} from well logging in Figure 4.4b; ^{*b} from Adams et al. (2003); ^{*c} from Ronald et al. (2019); ^{*d} from Fan et al. (2019)

4.4.3 Coupled fluid flow-geomechanics simulation and aftershocks analysis

The coupled flow-geomechanics simulation is conducted by using the COMSOL finite element software program to quantitatively characterize the poroelastic response surrounding the seismogenic fault during HF operations (COMSOL Multiphysics, 2019). The Mohr-Coulomb failure criterion is then applied to determine the fault activation and forecast the aftershocks following the large earthquakes.

(1) Model initialization

The modeling domain extends horizontally by $3.5 \text{ km} \times 5.5 \text{ km}$ and vertically from -2.7 km to -4.1 km (true vertical depth). This geometry is partitioned by eight corresponding formations, shown in Table 4.1. Three horizontal wells are set at a depth of 3400 m in an N-S trending orientation. The heights of hydraulic fractures are assigned to 44.9 m with the strike of NE 45° , respectively. The fracture half-length and width are calculated by the PKN model. Five inferred faults are also introduced into the model with

the conduit-barrier pattern. The thickness of damage zones and fault core is set at 20 m and 5 m, respectively. The hydraulic and mechanical parameters used in the coupled process are listed in Table 4.1. Figure 4.5 shows the 3D view of the coupled model, including related formations, horizontal wells, hydraulic fractures, and inferred faults.

The initial and boundary conditions are also defined for the coupled simulation. First, the original fluid system is assumed to be in a state of hydrostatic equilibrium. The initial stress tensor and pore pressure agree with the calculated results in Section 4.2.1. The injection rate for each stage of well A, B, and C are assigned to an average value of 9.58, 9.42, 8.36 m³/min, respectively. This injection source would act as a mechanical load in the simulation. After solving for the volumetric strain (ϵ) in the coupled process, the real-time deformation-dependent porosity and permeability would be derived based on Equations (8) and (9). A zero-flow rate boundary is applied in the model. The top surface is defined to be in a state of traction-free, whereas the displacement at the lateral boundaries and the bottom surface is assigned to be zero (Fan et al., 2019). Under this boundary condition, the triaxial stress state will be simplified to a monoaxial one. There is only one independent in-situ stress, the overburden stress (S_v), on which the other two principal stresses (S_{Hmax} and S_{Hmin}) are dependent. Next, the physics-controlled mesh is applied to the model, with a refined mesh in the vicinity of the hydraulic fractures and fault zone. Finally, the integrated simulation that coupled solid mechanics and fluid flow is conducted to characterize changes of pore pressure and stress tensor during and after fracturing stimulation.

Figure 4.5. Three-dimensional view of the coupled model used for coupled simulation. The block model is partitioned by five basement-rooted faults and eight stratigraphic layers. The wells, faults, and hydraulic fractures are all embedded in the model. Two yellow lines show two vertical profiles in Figure 4.6b and Figure 4.7b.

(2) Trigger mechanism of Mw 3.6 earthquake swarm

Figure 6a shows the simulated basal pore pressure changes (ΔP) at $t = 40$ days of northern HF operations. The wellbore pressure within the hydraulic fractures is calculated to be 5.9 MPa on average via Equation (4-3). It is shown that the damage zone (injection side of the fault) of Fault 1 and Fault 2 act as hydraulic conduits for pressure diffusion along the fault, whereas the fault core function as impermeable barriers for fault-crossing diffusion. By contrast, the pressure diffuses along both sides of Fault 5, owing to the direct connection between both sides of damage zones and related hydraulic fractures. Next, the ΔCFS is derived from the changes of both simulated pore pressure and poroelastic stress

using Equation (13). Figure 4.6b shows a detailed cross-sectional (C-C' in Figure 4.5) view of ΔCFS on Fault 1 at $t = 20, 30$, and 40 days after the onset of HF operations. The ΔCFS indicates that injected fluids approached Fault 1 through hydraulic fractures and diffused downwards along the high-permeability damage zone to the basement. On 24 January 2015 ($t=40$ days), the maximum ΔCFS in the basement reaches up to 0.46 MPa, exceeding the critical value and activates Fault 1. Moreover, the ΔP in the basement is simulated to be 2.3 MPa, surpassing the critical value of 2.0 MPa in the Mohr's cycle to cause the fault slip (Figure 4.4a). This large ΔP is attributed to the fact that the 19th-22nd stage hydraulic fractures of Well B are directly connected with Fault 1 (Figures 4.3c-3d). Therefore, the injected fracturing fluid could directly flow into the inferred fault plane, and the pressure would accumulate in the basement as treatments continue. By comparing both changes in pore pressure and stress tensors, it is shown that the increase in pore pressure during HF operations played the first-order role in fault activation in this case. Similarly, ΔCFS on Fault 2 and Fault 5 during specific stage completions reach 0.31 MPa and 0.35 MPa, respectively, and activate both faults accordingly. Moreover, based on the empirical relations between cumulative injection and moment magnitude (Mcgarr, 2014), the M_w 3.6 earthquake responds to a total injection of approximately $8,500 \text{ m}^3$, which occupies only 14.9% of the actual net injection volume of $56,872 \text{ m}^3$ in this case (Figure 4.6e).

The aftershocks following the M_w 3.6 mainshock are analyzed by using the Coulomb failure criterion. The Coulomb 3.3 software program is employed to compute ΔCFS surrounding Fault 1 after the mainshock event (Toda et al., 2011). Specifically, Fault 1 is first assigned as the fault that receives the Coulomb failure stress triggered by the M_w 3.6 mainshock. The focal properties with a strike of 176° , a dip of 83° , and a rake of 135°

(Zhang et al., 2016) are introduced into the Coulomb simulation. The displacement of Fault 1 is assumed to be uniformly distributed to simplify the simulation. The average slip displacement and effective friction coefficient are set with 0.25 and 0.4, respectively (Eyre et al., 2019; Zhao, 2018). Figure 4.6c shows the simulated ΔCFS right after the M_w 3.6 event in the basement. The mainshock induces a positive ΔCFS region (0.18 MPa at maximum) in the north end of Fault 1. The actual aftershock events (green balls) concentrate within this positive region, with a magnitude range of -0.13 to 1.76. Moreover, the ΔCFS and its constituents (e.g., $\Delta\tau$, $\Delta\sigma_n'$ and ΔP_{ep}) on Fault 1 after the mainshock event is shown in Figure 4.6d. It is found that the excess pore pressure P_{ep} is increasing slightly due to the continuing pressure diffusion along the fault despite the shut-in of operations. The reduced load-carrying capacity of the Fault 1 plane leads to a decrease in the effective normal stress, whereas the hydraulic fracture propagation increases the shear stress τ after the mainshock event. Simultaneously, the south segment of Fault 1 is located in the negative ΔCFS region (-0.2 MPa at minimum), where the fault slip is inhibited. However, along with the shut-in of hydraulic operations and the occurrence of aftershocks, this negative ΔCFS would vanish gradually, and thus the stress state surrounding Fault 1 would converge to the original stress state. As shown in Figure 4.6d, ΔCFS and its constituents on the fault converge on zero lines after the occurrence of aftershocks, suggesting the fault would not further slip within the basement in this scenario.

Figure 4.6. (a) Simulated pore pressure changes (ΔP) in the basement at $t = 40$ days after the onset of HF operations for well A and well B. Two horizontal wells are projected to the basement. (b) Detailed cross-sectional (C-C' in Figure 4.5) view of ΔCFS on Fault 1 at $t = 20, 30$, and 40 days, respectively. (c) Simulation results in terms of ΔCFS due to the $M_w 3.6$ mainshock in the basement. The majority of subsequent events cluster in the region with a positive ΔCFS . (d) ΔCFS , $\Delta \tau$, $\Delta \sigma_n'$ and ΔP_{ep} on Fault 1 after the mainshock and aftershocks. (e) The empirical relations between net injection volume and seismic moment magnitude (McGarr, 2014). These empirical estimations of net injection volume are not consistent with the actual volumes, indicating this plot is not adaptable for both cases in this work.

(3) Trigger mechanism of Mw 4.1 earthquake swarm

On 12 January 2016, the red-light Mw 4.1 earthquake nucleated during the 26th stage completions for well C, and fifteen events occurred sequentially in three days (Figure 4.1c). These clusters all shift to the top Winterburn Formation rather than in the basement. Figure 4.7a shows the simulated ΔP in the top Winterburn formation at $t = 8$ days after the initiation of HF operations. The pressure changes only on one side of Fault 1, further validating its conduit-barrier property. Simultaneously, Fault 4 allows pressure to diffuse along both sides due to the direct connection between hydraulic fractures and the fault. Moreover, the total net injection is estimated to be approximately 45,000 m³ that responds to the magnitude of Mw 4.1 (Figure 4.6e). This estimated volume is far beyond the estimated net injection volume of 29,046 m³ mentioned in the field background section, indicating the empirical relations between net injection volume and the maximum moment magnitude are not adoptable in both cases with direct HF-fault hydraulic connections (Atkinson et al., 2016).

Figure 4.7b shows a detailed cross-sectional (D-D' in Figure 4.5) view of ΔCFS on Fault 1 at $t = 4, 6$, and 8 days, respectively, after the initiation of HF operations. The ΔCFS suggests that fluid pressure diffuses along one side of Fault 1 upward into the Winterburn formation. On 12 January 2015 ($t=8$ days), the maximum ΔCFS in the top Winterburn segment of Fault 1 reaches 0.51 MPa, which also surpasses the threshold value and reactivates Fault 1. Moreover, the ΔP increases up to 2.5 MPa that also exceeds the required value (2.0 MPa) to activate Fault 1 (Figure 4.4a). Moreover, based on the aftershock simulation using the Coulomb 3.3 software program, the ΔCFS surrounding Fault 1 after the Mw 4.1 event is plotted in Figure 4.7c. It is worth noting that all fifteen aftershocks are

located within the positive ΔCFS region, exhibiting an N-S trending lineament. Similarly, this mainshock generates a negative ΔCFS region on the left side of Fault 1, inhibiting further fault slip in the top Winterburn Formation.

Figure 4.7. (a) Simulated pore pressure changes (ΔP) in top Winterburn formation at $t = 8$ days after the initiation of operations for well C. Three horizontal wells were projected to the top formation. (b) Detailed cross-sectional (D-D' in Figure 4.5) view of CFS changes (ΔCFS) on Fault 1 at $t = 4, 6,$ and 8 days, respectively. (c) Simulated ΔCFS surrounding Fault 1 due to the $M_w 4.1$ mainshock in top formation. All aftershocks clustered in the region with a positive ΔCFS .

4.5 Discussion

Current strategies for mitigating risks of HF-induced seismicity focus primarily on controlling the distance between hydraulic fractures and known faults, as well as operational factors (e.g., pumped volume, rate, and pressure of fracturing fluid, cyclic soft stimulation) and injection depth (Ellsworth et al., 2013; Fan et al., 2016; Schultz et al.,

2018; Haddad and Eichhubl, 2020; Zang et al., 2019). In this work, the sensitivity analysis for the M_w 3.6 case is conducted to better understand the effects of HF-fault distance and operational factors on fault activation (Figure 4.8).

First, three cases are set with an HF-fault distance of 0 m (actual M_w 3.6 case), 100 m, and 200 m (Figure 4.8a). As shown in Figure 4.8b, the maximum ΔCFS in the basement is simulated to be only 0.11 MPa for the 100-m-distance case and 0.025 MPa for the 200-m-distance case, both less than the critical value and hence Fault 1 is not activated in both scenarios. However, in the 0-m-distance case, the maximum ΔCFS in the basement is 0.46 MPa, surpassing the critical value to cause the fault slip. It is shown that hydraulic communication between the known fault and the stimulated well is established in the 0-m-distance case, in comparison with no such communication in the other two cases. Therefore, the HF-fault distance should be optimized to mitigate the risks of fault activation. Next, another three cases are also analyzed, in which the treatment pressure and net injection volume are set with (1) 80 MPa, 56,872 m³ (actual M_w 3.6 case), (2) 80 MPa, 20,000 m³, and (3) 90 MPa, 20,000 m³. Figure 4.8c shows the simulated maximum ΔCFS in these three cases. It is found that the maximum ΔCFS in three cases reaches 0.46, 0.16, 0.29 MPa, respectively. Therefore, the maximum ΔCFS has been attributed to the high treatment pressure and a large amount of net injection volume. Overall, the selection of injection sites relative to the known fault is the predominant factor in the mitigation of potential HF-induced seismicity.

The coupled simulation results are sensitive to the permeability increase in the fractured area and its hydraulic connectivity with the fault. The Duvernay shale formation has been considered to have vertical transverse isotropic properties. Such properties, in

combination with the contrast between the maximum and minimum principal stress, impact the propagation of hydraulic fractures. Therefore, the assumption that hydraulic fractures propagated parallel to S_{Hmax} in this work is an approximation. In actual cases, the fracture width might be reduced, and hence the fracture permeability might be less than calculated. We conducted the coupled simulation and found that the lower permeability of the narrower fractured zone will generate a relatively lower ΔCFS in comparison with the original one. In addition, based on the simulation results, the stress perturbation is much less than pressure changes. Therefore, the matrix deformation related to stress perturbation has minimal effect on the simulation results. Moreover, we notice that the north seismicity events concentrated at the intersection zone between Fault 3 and Fault 5 (Figure 4.6a). Here we assume that Fault 5 is activated due to the hydraulic connection between well B and Fault 5, and Fault 3 is not activated. This is because if Fault 3 were activated, the corresponding seismicity magnitude would reach more than 4.0 based on the relation plot between fault length and the maximum magnitude (Zoback et al., 2012). The mechanisms of such an earthquake swarm could be further investigated if more available data is obtained.

Figure 4.8. (a) Fracturing design for sensitivity analysis. Cases are set with different HF-fault distances, treatment pressure, and net injection volume. (b-c) Simulated temporal ΔCFS at the nucleation site of M_w 3.6 event under different HF-Fault distance and operational parameters.

4.6 Summary

A coupled approach of fluid flow and rock geomechanics is proposed to quantitatively understand the poroelastic effects caused by hydraulically induced seismicity near Crooked Lake, Alberta. The 3D poroelastic simulation of the seismogenic fault zone is conducted to characterize the trigger mechanisms for two earthquake swarms.

- (1) The poroelastic effects on high-permeable damage zones of a conductive-barrier fault are responsible for fault reactivation in the Precambrian Basement and top

- Winterburn Formation. The empirical net injection- M_w relations are not adoptable in cases with direct HF-fault hydrological connections.
- (2) The pressure diffusion and stress perturbation owing to the injection volume of 11,914 m³ fluids cause the fault slip and trigger the M_w 3.6 earthquake in the basement 40 days after the onset of operations. The aftershocks events occurred in regions with a negative Coulomb failure stress formed by the mainshock poroelastic response. The negative ΔCFS in the south region would vanish gradually as fracturing operations proceeds.
 - (3) The stimulation of another well with approximately 8,500 m³ volume of fluid injection facilitates poroelastic effects on the fault damage zone in the top Winterburn Formation. The M_w 4.1 earthquake was reactivated at eight days after the initiation of treatments.
 - (4) Enlarging HF-Fault distance and reducing the fracturing job size could mitigate the potential seismicity risks. The selection of injection sites relative to the known fault is the predominant factor in mitigating the risks of HF-induced seismicity.

CHAPTER 5 CONTROLLING FACTORS OF HYDRAULIC FRACTURING-INDUCED SEISMICITY

In this chapter, we explore the controlling factors of hydraulic fracturing-induced seismicity based on two field cases in Western Canada. The Mw3.0 case near Fox Creek is investigated to quantify the effect of a hydrological connection between stimulated wells and associated seismogenic faults on hydraulic fracturing-induced seismicity. The poroelastic modeling of the ML 4.18 case is conducted to quantify the effects of different hydraulic, geomechanical, and operational parameters on hydraulically induced seismicity.

5.1 Influence of hydrological communication between basement-rooted faults and hydraulic fractures on induced seismicity: a case study³

Abstract

The mechanical conditions that allow seismogenic faults to be activated in distinctive positions and moments remain uncertain. An integrated approach is proposed to quantify the hydrological connection between stimulated wells and associated seismogenic faults during fracturing stimulation. A case study in Fox Creek, Alberta, was conducted to demonstrate the applicability of this integrated approach. Ant tracking was used to identify the subvertical basement-rooted faults from a three-dimensional seismic reflection survey. A coupled flow–geomechanics simulation was conducted to quantify the well–fault

³ Hui G., Chen, S., Gu F. et al., (2021e). Influence of hydrological communication between basement-rooted faults and hydraulic fractures on induced seismicity: A case study. *Journal of Petroleum Science and Engineering*, 206, 109040.

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hydraulic connection in terms of pore pressure diffusion and poroelastic stress perturbation during fracturing stimulation. Three identified basement-rooted faults were corroborated by the focal mechanisms and spatial distribution of induced seismicity events. The negative shear stress gradient indicates the downward shear growth during hydraulic connections. The induced seismicity was triggered by fluid diffusion through hydraulic fractures along high-permeability fault damage zones downwards into the basement. This basal fault slip was attributed primarily to the elevated pore pressure along the fault plane in response to fracturing fluid injection. The moderate distance (879 m for NS-oriented wells and 749 m for NW-SE-oriented wells) between the future horizontal wellbores and critically-stressed faults could mitigate the effects of well-fault hydraulic connection and reduce the seismicity risks.

5.1.1 Introduction

The rate of seismicity in the Western Canada Sedimentary Basin (WCSB) has increased notably since 2010, and the increase has been linked spatiotemporally to anthropogenic development of petroleum resources, including enhanced oil recovery in the Rocky Mountain House region (Wetmiller et al., 1986), wastewater disposal in the Brazeau River zone (Schultz et al., 2014) and hydraulic fracturing (HF) in the Fox Creek area (Schultz et al., 2015). Recently, several earthquakes of moderate-to-large magnitude have occurred in Fox Creek, and these have been attributed to HF treatments (Figure 5.1) (Atkinson et al., 2016; Bao & Eaton 2016; Wang et al., 2017; Eaton et al., 2018; Eyre et al., 2019; Hui et al., 2021a). Hydraulic fracturing involves injecting pressurized fluids into low-permeability hydrocarbon reservoirs to create open fracture networks, whereupon a fluid-pressure pathway (hydraulic fractures) is established, thereby allowing hydrocarbons to flow towards the wellbore to be produced. In Fox Creek, it is estimated that more than 600 horizontal wells have been stimulated hydraulically within the Duvernay Formation since June 2010 (Figure 5.1). Based on the statistics of treatment datasets, the cumulative

injection volume reached an average of 32 944 m³ per well. Such large-scale stimulations may be accompanied by large-magnitude-induced events (McGarr 2014; Schultz et al., 2018). However, only 6% of HF operations targeting the Duvernay Formation were associated with induced seismicity with moment magnitude $M_w > 3$ (Ghofrani & Atkinson 2020), necessitating to investigate site-specific subsurface geological and operational factors associated with HF-induced seismicity in this region (Schultz et al., 2018, 2020; Pawley et al., 2018).

Large-magnitude HF-induced seismicity is related to the activation of seismogenic faults. Typically, the underlying mechanical conditions that control seismogenic-fault activation during HF operations include (i) the injection rate, pressure and volume of fluids, (ii) the connection between faults and stimulated wells that transmits pressure diffusion and/or stress perturbation and (iii) the hydraulic and geomechanical properties of faults, reservoir, fluid and associated formations under subsurface conditions (Ellsworth et al., 2013; Galloway et al., 2018; Tan et al., 2020). Previously, HF-induced seismicity has been characterized using seismological or geomechanical approaches (Bao & Eaton 2016). However, the intricacy of site-specific subsurface structures and geomechanical features means that the potential hydrological connections between the stimulated wells and seismogenic faults during HF are yet to be investigated properly.

This paper investigates the geological indication of fault activation and quantifies the effect of hydrological connections between seismogenic faults and stimulated wells on HF-induced seismicity in Fox Creek. Ant tracking is used to identify basement-rooted faults (BRFs) from a three-dimensional (3D) seismic reflection survey, and the faulting stress regime, fault geomechanical properties and architecture are characterized. A coupled

flow–geomechanics simulation is conducted to quantify the pore pressure diffusion and poroelastic stress perturbation during and after HF stimulations. The gained understanding of hydraulic connections may provide insights that will mitigate future seismic risks in Fox Creek.

Figure 5.1. Map of recorded seismicity and fracturing wells in Fox Creek. The base map shows the elevation of the Duvernay Formation (beneath sea level). Red circles denote historical seismicity of $M_w \geq 2.5$ up to 2020/01/31 in Fox Creek (www.inducedseismicity.ca/catalogues; last accessed on 2020/08/27). The dashed pink line represents the outline of the Duvernay Formation in the studied region. The white polygon marks the position of Fox Creek. The magnitude-scaled beachballs show the focal mechanisms of reported large-magnitude events (Schultz et al., 2017; Wang et al., 2018; Zhang et al., 2019). The black lines represent the trajectories of fracturing wells targeting the Duvernay Formation. The blue circles show the cumulative injection of fracturing fluid per well. The blue rectangle marks the present studied case ($M_w = 3.0$ event on 2015/02/08). The inner map shows the location of Fox Creek.

5.1.2 Datasets

The occurrence of induced seismicity began in December 2013 in Fox Creek (Schultz et al., 2015). More than six earthquakes with $M_w > 3.0$ occurred in this region from January 2015 to November 2016 (Figure 5.1). The focal mechanisms of these six events exhibit similar strikes trending approximately North-South (N–S), indicating the possible existence of seismogenic faults associated with these events. Additionally, the geological susceptibility of induced seismicity in Fox Creek has been attributed primarily to (i) basement proximity, (ii) the formation overpressure, (iii) the magnitude of minimum principal stress (S_{hmin}) and (iv) proximity to the Swan Hills reef margins (Pawley et al., 2018; Eaton & Schultz 2018; Schultz et al., 2016). Furthermore, 606 horizontal wells have been subjected to HF treatments with an average injection rate of $9.5 \text{ m}^3/\text{min}$, a cumulative injected volume of $32\,944 \text{ m}^3$ and a proppant weight per well of 4009 t, thereby making the stimulation process apparently seismogenic. Overall, both operational factors and geological susceptibility are primarily responsible for HF-induced seismicity in Fox Creek (Schultz et al., 2018; Pawley et al., 2018).

In the present study, the $M_w = 3.0$ earthquake swarm [blue rectangle in Figure 5.1; Cluster 6 in the datasets of Bao & Eaton (2016)] is scrutinized to explore the spatiotemporal relationships among induced clusters, structural features and HF stimulations. The regional seismic networks are estimated to have detected 109 induced events during HF operations, with moment magnitude ranging from 1.0 to 3.0. The well completion and treatment data of associated wells are available through the public database. The catalog of microseismicity is the source from prior works (Bao and Eaton, 2016). The well-logging data of this horizontal well and nearby vertical wells were also collected from the database,

including the density log and S-wave and P-wave velocity log data. Figure 5.2 shows this case in detail, including the spatiotemporal characterization of the earthquake swarm and HF operations. During 5–14 February 2015, 20 stage completions were performed northwards on an N–S-trending horizontal well. The southern cluster (blue balls in Figure 5.2b) was activated at an average offset of 200 m from the wellbore. An $M_w = 3.0$ event within this cluster occurred on 8 February, with an approximately N–S-trending focal mechanism (Schultz et al., 2017). The activation of this cluster continued for up to 40 h to 8 February (the onset of stage-completion 6 in Figure 5.2a). As operations continued, the eastern cluster (green balls in Figure 5.2b) was activated with roughly East-West (E–W) trending. This cluster lasted for 100 h with $M_w = 1.19$ – 2.9 . After the end of 15th stage completion, the northern cluster was activated 300 m away from the wellbore with $M_w = 1.49$ – 3.0 . Throughout the HF operations, the average pumped pressure, pumped rate and cumulative volume reached 55.8 MPa, 8.7 m³/min and 38 078 m³, respectively. Based on the focal depth inversions, the hypocentres for these clusters were located primarily 200–1300 m beneath the treatment layer. Moreover, the *b* value (slope of the magnitude–frequency distribution) for these clusters is estimated to be 0.84 (Figure 5.2a), which, combined with the lineament features of the induced events, indicates activation of the nearby pre-existing faults (Eaton et al., 2014). In addition, 3D multicomponent reflection seismic data is available in the studied region. The prestack inversion of the 3D seismic data has been well documented in prior works (Ronald et al., 2019).

Figure 5.2 Detailed view of studied $M_w = 3.0$ earthquake clusters. (a) Time sequence showing induced clusters and treatment data for the horizontal well. The circles represent induced events colored by time. The vertical colored line shows the injection volume for each stage. The red horizontal line denotes the cumulative injection volume over time. The 6th and 15th stages divide the swarm into three clusters. Time ranges from 2015/02/05 to 2015/02/17. (b–d) Map and vertical cross-section views of earthquake distributions after double-difference relocation (Bao & Eaton 2016). The NE 45°-oriented grey lines overlapping the horizontal well indicate the simulated hydraulic fractures mentioned later. The beachballs show the focal mechanism of the $M_w = 3.0$ event (Schultz et al., 2017). These induced events are colored by date and scaled by magnitude.

5.1.3 Methods

(1) Fault identification and characterization, and propagation of hydraulic fractures

Identification of basement-rooted faults. The availability of 3D seismic data provides an opportunity to identify the pre-existing faults in the studied region. Specifically, the associated formations are interpreted first from the 3D seismic reflection data using the synthetic-seismogram-tie for key wells (Ronald et al., 2019). Here, the ant tracking approach is adopted to identify the pre-existing faults with small offsets via populating pre-processed 3D seismic data (Pedersen et al., 2002), which helps explore the potential relationships between induced seismicity and small-scale structural features. The ant-tracking workflow comprises the following main sequential steps, namely (i) seismic conditioning, (ii) edge detection and enhancement and (iii) auto-track interpretation (Adel et al., 2016). The interpretation results are validated further by the focal mechanisms of the induced seismicity (Zhang et al., 2019). However, it is also worth noting that not all faults are identified prior to hydraulic fracturing operations, even with the 3D seismic data (Atkinson et al., 2016).

In situ stress, fault architecture and geomechanical properties. Previous work has shown that most of the seismogenic faults in Fox Creek involve a strike-slip mechanism (Schutz et al., 2017; Shen et al., 2019), which is corroborated by comparing the magnitudes of the maximum principal stress (S_{Hmax}), the minimum principal stress (S_{hmin}) and the vertical stress (S_v) (Zoback 2007). The full stress tensors and pore pressure are estimated from fracturing-treatment data and density logs (Zoback 2007), which are then incorporated into the following coupled model. Specifically, the gradient of S_v is determined by the vertical integration of density logs for nearby wells in the studied region. The gradients of S_{hmin} and formation pore pressure (P_p) are estimated respectively from the closure pressure and the reservoir pressure at the end of stage completion (Yew & Weng

1997). The gradient of S_{Hmax} is derived from $S_{Hmax} = 3S_{hmin} - 2P_p$ (Zoback 2007). The calculation result of S_{Hmax} is further corroborated by prior works in this region (Shen et al., 2019; Eyre et al., 2019). Moreover, a typical fault zone comprises a low-permeability fault core and two surrounding highly fractured damage zones (Chester et al., 1993). This conduit-barrier attribute of faults—acting as barriers for cross-fault flow but as conduits for along-fault diffusion—could have an essential effect on the spatiotemporal patterns of induced seismicity. Additionally, the geomechanical parameters of formations and faults—such as Poisson’s ratio and Young’s modulus for each formation—can be obtained from the velocities and density logs of nearby key wells (Ronald et al., 2019).

Propagation of hydraulic fractures. The propagation of hydraulic fractures can be simulated by matching the history of the net operational pressure during HF operations. Based on the treatment and reservoir dataset, the FRACPRO software program is used to simulate the HF geometry (Hui et al., 2021a). Specifically, the HF database is first constructed by integrating the treatment pressure, slurry rate and proppant concentration, as well as the wellbore structure and formation parameters under subsurface conditions. The fracturing fluid and proppant type are then selected according to the field conditions to compute the friction loss and closure pressure. Finally, the net pressure is subjected to history matching to simulate the HF length and width. The simulated propagation of hydraulic fractures helps to determine whether hydrological communication between the stimulated well and inferred faults is established during fracturing treatments.

(2) Coupled poroelastic modeling and fault-activation criterion

Fluid diffusion and stress perturbation in a porous medium can be characterized using linear poroelasticity theory (Wang 2000). Wang & Kumpel (2003) showed that the poroelastic process could be characterized by two coupled equations, namely

$$G\nabla^2\vec{u} + \frac{G}{1-2\nu}\nabla\epsilon - \alpha\nabla P_p = \vec{f}(\vec{x}, t), \quad (5-1)$$

$$\frac{1}{M}\frac{\partial P_p}{\partial t} + \alpha\frac{\partial\epsilon}{\partial t} - \nabla \cdot \left(\frac{k}{\eta}\nabla P_p\right) = q(\vec{x}, t), \quad (5-2)$$

where G is the shear modulus, u is the displacement vector, ν is Poisson's ratio, ϵ is the volumetric strain, α is Biot's coefficient, $\vec{f}(\vec{x}, t)$ is the body force per unit volume on the solid matrix, P_p is the pore pressure, M is the Biot modulus, k is the matrix permeability, η is the dynamic fluid viscosity, ρ is the fluid density, z is the measured depth and $q(\vec{x}, t)$ is the volume injection source rate.

Equations (1) and (2) apply to fluid injection from a point source into a homogeneous, isotropic and poroelastic medium (Altmann et al., 2010) and can be solved using the finite-element method. Moreover, because Skempton's coefficient (B) and the undrained Poisson's ratio (ν_u) are measured easily in the laboratory, the parameters in Eqs. (1) and (2) can be expressed in terms of B and ν_u as (Wang 2000; Wang & Kumpel 2003)

$$\alpha = \frac{3(\nu_u - \nu)}{(1-2\nu)(1+\nu_u)B}, \quad (5-3)$$

$$\frac{1}{M} = \frac{9(1-2\nu_u)(\nu_u - \nu)}{2(1-2\nu)(1+\nu_u)^2 GB^2}, \quad (5-4)$$

$$\frac{k}{\eta} = \frac{9(1-\nu_u)(\nu_u-\nu)D}{2(1-\nu)(1+\nu_u)^2 GB^2}, \quad (5-5)$$

where ν_u is the undrained Poisson's ratio, B is Skempton's coefficient, and D is the hydraulic diffusivity.

After simulating the changes in pore pressure and in situ stress during HF operations, the Mohr-Coulomb failure criterion is generally used to determine the spatiotemporal activation of the associated faults (Catalli et al., 2013; King & Deves 2015). To characterize the stress states of those faults, the Coulomb failure stress (CFS) is calculated in terms of the shear and normal stresses using (Zoback 2007):

$$\Delta CFS = (\Delta\tau - \mu\Delta\sigma_n) + \mu\Delta p_p, \quad (5-6)$$

$$\sigma_n' = \frac{1}{2}(\sigma_1 + \sigma_3) - \frac{1}{2}(\sigma_1 - \sigma_3)\cos(2\beta) - p_p, \quad (5-7)$$

$$\tau^l = \frac{1}{2}(\sigma_1 - \sigma_3)\sin(2\beta), \quad (5-8)$$

$$\tau^r = -\frac{1}{2}(\sigma_1 - \sigma_3)\sin(2\beta), \quad (5-9)$$

where Δ denotes the changes in each parameter, CFS is the Coulomb failure stress, τ is the shear stress (positive in the slipping direction), σ_n' is the effective normal stress (positive in the extensional direction), μ is the friction coefficient, σ_1 and σ_3 are the magnitudes of S_{Hmax} and S_{hmin} , respectively, τ^r and τ^l are the shear stresses in the right-lateral and left-lateral motions of the fault, respectively, and β is the angle between the S_{Hmax} orientation and the fault strike.

The shear stress gradient used to determine the downward or upward shear growth can be derived from the following equations (Pine et al., 1983):

$$G_1' = \frac{d\tau_f}{dD} - \frac{d\tau}{dD}, \quad (5-10)$$

$$\tau_f = \sigma_n' \tan \Phi, \quad (5-11)$$

$$G_1' = G' \tan \Phi, \quad (5-12)$$

where G_1' and G' are the differential shear gradient; τ_f and τ are peaks and normal shear stress; D denotes the depth below the ground surface; ϕ is the friction angle; β represents the angle between the fault plane and S_{Hmax} direction; σ_1 and σ_2 are the maximum and minimum principal stress. The positive G' corresponds to the upward shear growth, while the negative one corresponds to the downward shear growth.

Based on Eqs. (6)–(9), the two-dimensional Mohr circle is plotted to depict the stress state of the seismogenic fault prior to and during fracturing operations, as well as to determine the spatiotemporal activation of pre-existing faults during fracturing operations. In the present study, the COMSOL Multiphysics finite-element software was used to simulate the spatial and temporal changes in pore pressure and poroelastic stress surrounding the related faults (COMSOL Multiphysics 2019). Specifically, we select the fluid flow in the Darcy's Law interface and elastic porous media deformation in the Solid Mechanics in the COMSOL program. The injection pressure per stage could be assigned to simulate the pore pressure changes within and surrounding the fractures and faults, whereas the Mechanics module could describe the solid displacement, stress and strain changes during fluids injection. The model initialization is accomplished by setting model geometry, initial and boundary conditions, and introducing the hydraulic and geomechanical parameters. Finally, the Mohr-Coulomb failure criterion is applied to

determine the spatiotemporal activation of these faults during HF operations (Zoback 2007; Hui et al., 2021b).

5.1.4 Results

(1) Characterization of basement-rooted faults and hydraulic fracture network

Identification of basement-rooted faults. The Duvernay, Muskeg and Cambrian Formations are interpreted and shown in Figures 5.3a and 3b. Ant tracking is then used to track small-offsets faults by means of the workflow described in Section 3. Figure 5.3c–e show horizontal cross-sectional views of the ant-tracking attributes in the Duvernay, Cambrian and Precambrian Formations, respectively. As can be seen, most of the events are clustered in the basement, which is consistent with the spatial distribution of intricate fault networks.

Based on our analysis for the link between faults and earthquakes, three subvertical faults (Faults 1–3) are identified by ant tracking, all extending from the Precambrian basement upwards through the Duvernay Formation (Figure 5.3b). Fault 1 is more than 800-m long with an NW–SE-trending strike. The strike and dip of Fault 1 are approximately 175° and 89° , respectively, consistent with the focal mechanism using double-couple grid searching (Schultz et al., 2017). Faults 2 and 3 follow the same basement-rooted pattern and have lengths of 820 and 590 m, respectively, and dips of 89° and 88° , respectively. Furthermore, the induced events are distributed mainly along two sides of three inferred faults, indicating that the majority of the induced seismicity was nucleated in the damage zones of these faults. The existence of inferred faults provides a

geological indication that hydraulic communication was established among the faults and stimulated during HF operations on the horizontal well.

Figure 5.3 Detailed views of fault interpretation via ant tracking. (a) Raw A–A' vertical cross-section of seismic reflection data. The pink line denotes the trajectory of the horizontal well. (b) Interpreted A–A' cross-section data. Locations of earthquakes (blue circles), horizontal well (pink line), formation marks (sub-horizontal colored lines) and three interpreted faults (subvertical black line) are shown. The induced seismicity is scaled by magnitude. (c–e) Horizontal cross-section of ant-tracking attributes (yellow area) for the Muskeg, Cambrian and Precambrian Formation. Colored balls denote the induced seismicity above the corresponding formation.

Fault architecture, original stress state and geomechanical and hydraulic properties.

The properties of these inferred faults are also investigated in terms of fault architecture,

faulting stress regime and geomechanical properties. Based on the ant-tracking interpretation, the width of the damage zone for Faults 1–3 (perpendicular to the strike) is approximately 50, 50 and 40 m, respectively. In the present work, the thickness ratio of the damage zone (one side) to the inner fault core is set to 4:1 based on the distribution of induced events along both sides of the damage zones, and the permeabilities of the fault core and damage zones are set empirically to 10^{-20} and 10^{-14} m^2 , respectively (Yehya et al., 2018; Fan et al., 2019). Note that the permeability of the fault differs from that of the formations that it transected because of the different lithology and fracture development between fault and formations.

Based on the publicly World Stress Map (WSM database release 2016), the direction of S_{Hmax} is taken as NE 45° , consistent with previous work on stress orientations near Fox Creek (Reiter et al., 2014; Shen et al., 2019). Based on the well-logging and treatment data, the gradients of S_v , P_p , and S_{hmin} are estimated to be 24.6 ± 0.24 , 16.4 and $20.78 \pm 0.59 \text{ kPa/m}$, respectively. Thus, the gradient of S_{Hmax} is calculated to be 29.5 kPa/m with an uncertainty interval of -1.70 to $+2.15 \text{ kPa/m}$. These results are consistent with previous work (Eaton & Schultz 2018; Zhang et al., 2019; Eyre et al., 2019; Shen et al., 2019). Therefore, the three BRFs in the present work involve a strike-slip mechanism ($S_{Hmax} \geq S_v \geq S_{hmin}$) (Zoback 2007). Under this mechanism, the conduit-barrier properties of faults account for their nucleation position at the basement (Fan et al., 2019). In addition, the occurrence of induced seismicity has been attributed to the strike-slip motion of basement-rooted faults (Wang et al., 2017). Because the $M_w = 3.0$ event was attributed to the activation of Fault 1, only the changes in the stress state for Fault 1 are studied in the present work. Based on Eqs. (6)–(9), the two-dimensional Mohr circles used to characterize

the initial stress state of Fault 1 prior to HF treatments are plotted using the estimated full stress tensors (Figure 5.4). Two focal planes are shown, and the N–S plane is related to the $M_w = 3.0$ event based on the ant-tracking results. As can be seen, if the in situ stress changes are negligible, then an increase in pore pressure of 3.5 MPa is required to activate Fault 1 during HF treatments. Moreover, the shear stress gradient G is calculated to be -0.16 MPa/km, indicating the downward shear growth during hydraulic injections (Pine et al., 1983). The simulated pore pressure and stress changes are discussed in the following Section 4.2.

The geomechanical properties of related formations are determined to quantify the poroelastic effects during fracturing operations. The fault is assigned Young's modulus and Poisson's ratio of 10 GPa and 0.15, respectively, consistent with its empirical elastic properties (Haddad & Eichhubl 2020). The hydraulic properties (porosity and permeability) of the associated formations are taken from previous work (Adams et al., 2003). Table 5.1 lists the hydraulic and geomechanical rock properties of formations transected by the inferred faults. The ranges of Young's modulus and Poisson's ratio are 46.8–71 GPa and 0.20–0.31, respectively, and those of porosity and permeability are 0.02–0.1 and 3.94×10^{-19} to 6.3×10^{-16} m², respectively. Biot's coefficient (α) is 0.79 and 0.44 for high-permeability and low-permeability formations, respectively (Fan et al., 2016).

Figure 5.4 Mohr diagram for stress states of two focal planes. The pink line represents the Mohr-Coulomb failure line. The friction coefficient is $\mu = 0.6$ (Zhang et al., 2019). The contours (unit: MPa) within the Mohr circle indicate the calculated increase in pore pressure required to activate the faults. Based on the ant-tracking results, the N-S fault plane was activated during HF operations and triggered the $M_w = 3.0$ event. An estimated increase in pore pressure of 3.5 MPa is required to activate the N-S plane of Fault 1 during fracturing stimulations.

Table 5.1. Hydraulic and geomechanical properties for each formation

Formation	Thickness	ν	E	Porosity	Permeability	Biot coefficient
	[m]		[GPa]		$\log k$ [m^2]	
Ireton	160	0.20	46.8	0.05	-16.52	0.79
Duvernay	40	0.22	55	0.065	-18.40	0.44
Swan Hills	100	0.31	66	0.05	-16.03	0.79
Muskeg	100	0.28	71	0.083	-16.05	0.79
Cambrian	200	0.27	66	0.1	-15.22	0.79
Basement	1200	0.28	70	0.02	-16.8	0.79

Propagation of hydraulic fractures. Based on the treatment data of the horizontal fracturing well, we have used the FracPro software program to simulate the propagation of hydraulic fractures via the history-matching of the net pressure during HF operations. Three parameters are compared, including the injection volume per stage, the simulated fracture half-length and the corresponding induced events (Figure 5.5). The simulated hydraulic fractures are spatially related to the induced events (Figure 5.2b). Statistically, the fracture half-length is 64.1-182.5 m, with an average of 136.5 m. The average aperture width of the fractures is 0.019 m, corresponding to the permeability of $7.5 \times 10^{-12} \text{ m}^2$ based on empirical equations relating to fracture permeability and fracture width. This result contrasts sharply with the matrix permeability of $3.94 \times 10^{-19} \text{ m}^2$ in the shale-hosted Duvernay Formation, indicating that the enhanced permeability of hydraulic fractures would facilitate the pressure diffusion of fracturing fluids during HF operations.

The simulated fracture length via FracPro software is proportional to the injection volume per stage (Figure 5.5), which matches well with the PKN model (Hui et al., 2021b). Specifically, the half-length of the stage-7 fracture is calculated to be 64.1 m because of the low injection volume (640 m^3), corresponding to only three induced events of $M_w < 2$. By contrast, stage 20 is computed to be 182.5-m long under an injection volume of 2888 m^3 , leading to the nucleation of 25 earthquakes with an $M_w = 3.0$ event. Therefore, the operational factors have a significant effect on hydraulic connections between seismic faults and the stimulated well, which would account for the activation of Fault 1 due to pore-pressure diffusion and stress perturbation.

Figure 5.5 Comparison of injection volume per stage, simulated fracture half-length and corresponding induced events. The blue histogram shows the injection volume per stage. The orange line denotes the half-length of hydraulic fractures for each stage. The purple line represents the number of induced events corresponding to each stage.

(2) Quantification of well–fault hydrological communication

Coupled poroelastic modeling. The 3D finite-element model has dimensions of $2.5 \text{ km} \times 3.5 \text{ km} \times 1.8 \text{ km}$ in the x, y and z directions, respectively, with the bottom in the z-direction at -4.1 km . This geometry is partitioned by three BRFs and six layers. The Ireton, Duvernay, Swan Hills, Muskeg, Cambrian and Basement Formations are set from top to bottom with thicknesses of 160, 40, 100, 100, 200 and 1200 m, respectively. The N–S-trending horizontal well is located at -2.5 km below sea level. The 20-stage NE 45° -oriented hydraulic fractures are set with their simulated lengths and widths. Three inferred faults with seismically derived parameters (height, width, strike, dip) are also embedded in the 3D block model. The thickness proportion of the fault core and two damage zones is set as 1:4:4. The hydraulic and geomechanical parameters used in the model come from

Table 5.1. The density, compressibility and dynamic viscosity of the fracturing fluid are set as 1200 kg/m^3 , $4.6 \times 10^{-10} \text{ Pa}^{-1}$ and $0.4 \text{ mPa}\cdot\text{s}$, respectively. Figure 5.6a shows the initialization of the poroelastic model used in the following simulation.

Initial and boundary conditions are also set for the poroelastic model. The initial pore pressure and stress tensors by depth are assigned to the calculated results. The fracturing fluids are injected into the fracturing stages of the well over time as the injection source. The injection rate for each stage is obtained from actual treatment data. The boundaries of the block model are fixed: the top surface is traction-free, and the lateral boundaries and bottom surface have zero displacements. The poroelastic model is given a physics-controlled mesh with a refined mesh in the hydraulic fractures and fault zones (Figure 5.6b). A simulation that couples the solid mechanics and fluid flow in the medium is then conducted to compute the pressure and stress changes during the HF operations of the horizontal well.

Figure 5.6 Initialization of coupled model. (a) 3D view of block model. The model is partitioned by three inferred faults and six horizontal layers. The horizontal well with 20-stage hydraulic fractures is embedded

in the model. The dashed red line shows the vertical C–C' cross-section, as shown in Figure 5.7. (b) 3D mesh using triangular elements. The mesh is refined within and surrounding the fractures and faults.

Hydrological connection and fault activation. Figure 5.7a shows the horizontal cross-section view of the simulated pore-pressure changes (ΔP_p) at the basement of Fault 1 at $t = 80$ h after the onset of HF treatments. As can be seen, Fault 1 acts as a conduit for cross-fault fluid flow, given that the pore-pressure changes increase sharply on both sides of the damage zones of Fault 1. This conduit pattern is attributed to the connection of fluid pressure through hydraulic fractures towards the damage zones and the lower proportion of fault core with respect to the whole fault width (1:9). It is also consistent with the spatial distributions of the southern clusters surrounding Fault 1, indicating that the associated fluid pressure diffuses through hydraulic fractures downwards along the high-permeability damage zones of Fault 1.

Figure 5.7b illustrates the vertical cross-section C–C', showing the changes in the poroelastic parameters of Fault 1. The changes in pore pressure, effective normal stress, shear stress and ΔCFS at the basement part of Fault 1 reached 3.9, 0.36, 0.14 and 1.53 MPa, respectively. Based on the simulated and updated effective normal stress ($\Delta \sigma_n - \Delta P = -3.54$ MPa) and shear stress ($\tau = 0.14$ MPa), Fault 1 would exceed the Coulomb failure line in the updated Mohr circle using the above-simulated results (Figure 5.4). The high permeability of the damage zones in Fault 1 facilitates the vertical diffusivity of the fracturing fluid for the horizontal well. Comparing the pore-pressure changes and in situ stress changes for Fault 1 shows that the pore-pressure increase remains the predominant factor influencing fault activation in this case. Moreover, there is another

M_w3.0 event occurred on 15 February 2015, one day after the last stage of the fracturing well (Figure 5.2a). Based on the spatial distribution between hydraulic fractures and pre-existing faults, the triggering mechanism of this event is similar to that of the previous M_w3.0 event (Figure 5.8a). That is, the fluid pressure diffuses towards the basement-rooted fault and causes Fault 3 to activate. Therefore, reducing the hydraulic communication between the stimulated well and known faults is essential for mitigating the seismic risks in the Fox Creek region.

Figure 5.7. (a) Horizontal cross-section at a depth of 3800 m shows simulated pore-pressure changes at the basement of Fault 1 at $t = 80$ h after the onset of HF operations for the horizontal well. The horizontal wells and hydraulic fractures within the Duvernay Formation are projected to the basal map. The blue cross denotes the vertical fault plane in cross-section C–C'. (b) Fault plane in cross-section C–C' shows changes of pore pressure, effective normal stress, shear stress and CFS for Fault 1 at $t = 80$ h after onset of HF operations. The right column shows the relative contribution of μP_p (red), $\mu \sigma_n$ (green) and τ (purple) to ΔCFS , where pore pressure changes contribute most.

5.1.5 Discussion

(1) Operational mitigation strategies of seismicity risks

The proper real-time monitoring with downhole and/or surface microseismicity has been performed during and after HF operations in the WCSB. The traffic light system regulated by Alberta Energy Regulator (AER) has been utilized to monitor the fracturing treatments. The current strategies for mitigating potential HF-induced seismicity concentrate primarily on selecting the stimulation site with respect to pre-existing faults, treatment parameters (pumped volume, rate and pressure) and injection depth above the basement (Schultz et al., 2018). Of these strategies, increasing the horizontal distances between the horizontal wellbore and known BRFs has shown field practicability for mitigating seismic risks in the Fox Creek region (Wilson et al., 2018).

An inferred large fault system (whose northern part is Fault 1) extends southwards up to 3 km in a SE–NW trending strike (Figure 5.8a). Another N–S-trending horizontal well was drilled 500 m away to the west of the fault, compared with 150 m in the $M_w = 3.0$ case. In November 2016, the southern well was subjected to HF operations northwards along the wellbore while some induced events clustered in the vicinity of the fault, 600 m to the east from the southern well. These induced events were concentrated primarily within the stimulated formation, in sharp contrast to the basement depth for the northern $M_w = 3.0$ cluster (Figure 5.8d). Moreover, the focal mechanism of a maximum $M_w = 1.2$ earthquake indicates the seismogenic fault strike of $NE\ 28.2 \pm 8.3^\circ$ (Zhang et al., 2019). The inconsistency between the two focal mechanisms for the northern and southern swarms suggests that the large fault was not activated in the southern case. Moreover, with a maximum magnitude of only $M_w = 1.2$, the southern cluster exhibits a different

spatiotemporal pattern than that of the northern cluster (Figure 5.8a–d). Instead, a small-scale natural fracture is inferred between the new wellbore and the fault (the lineament in the dashed circle in Figure 5.8a) and was activated because of its hydraulic connection with the southern well. The maximum CFS change around the fault is simulated to be only 0.15 MPa (Figure 5.9c), less than the 1.53 MPa for the northern swarm.

A 20-m-distance is set to analyze the effect of distance along the fault from the HF operations while the 270 m of HF-fault distance follows the actual case. Only one-third of the inferred fault has been affected by the poroelastic process (Figure 5.9b), and the ΔP_p for the rest of the fault is approximately zero. The distribution of ΔP_p along the fault is attributed to the factors such as fault permeability and thickness of damage zones. In the case of 270 m as the HF-fault distance, the ΔCFS and ΔP_p maintain a low value as treatments continue (Figure 5.9c). However, in the scenario with 20m of HF-fault-distance, ΔCFS and ΔP_p keep increasing, indicating that the pore pressure diffuses through hydraulic fractures towards the inferred faults.

Figure 5.8. Field case using mitigation strategy of increasing well–fault distance. (a) Horizontal cross-section of ant-tracking attributes at the top of Duvernay Formation. Another N–S-oriented new horizontal well was subjected to HF operations in November 2016. The green beach ball shows the focal mechanism of a maximum $M_w = 1.2$ earthquake (Zhang et al., 2019). The lineament in the dashed circle denotes a possible natural fracture that was responsible for the southern cluster. (b, c) Histograms and cumulative features of magnitude distribution for northern and southern clusters, respectively. The legend shows the b value and sample numbers for each cluster. (d) Vertical F–F' section views of earthquake distributions. The balls represent induced seismicity, colored by time and scaled by magnitude. The top and bottom color bars show the time range for the two clusters.

Figure 5. 9. (a-b) The spatial ΔP_p with HF-fault distance of 270m and 20m, respectively, after stage completions. The nucleation position is marked by the pink cross. (d) The ΔCFS and ΔP_p at the position indicated by the pink cross under two different HF-fault distances. The red and dashed red line corresponds to the HF-fault distance of 20m, while the blue and dashed blue line corresponds to the distance of 270m.

(2) Safe distance between horizontal wellbores and potential faults

Figure 5.10 shows some field cases that recorded HF-induced seismicity during fracturing operations of the fracturing horizontal wells. Specifically, we collect the filed cases of SS6-SS12 (Schultz et al., 2017), FC5 (Bao and Eaton, 2016), and ToC2ME (Eaton et al., 2018) including the fracturing wells and spatial-temporally related induced

seismicity events. We assume that the hydraulic fractures of these wells propagated along the direction of the maximum principal stress (NE 45°), following the PKN model in the spatial propagation (Hui et al., 2021b), and the results are shown in Figure 5.10a-10b. It is noted that the induced seismicity events have a distinctive spatial distribution in the NS-oriented wells (ToC2ME, SS6, SS9, SS10 and SS17) and NW-SE-oriented wells (SS7, SS8, SS11, SS12 and FC5). The injection volume for the NS-oriented and NW-SE-oriented fracturing wells and the distance to the furthest microseismic events are investigated and the results are shown in Figure 5.10c-10d. For the NW-SE-oriented wells, a statistically empirical relationship ($R^2 = 0.874$) exists between injection volume and distance to the furthest detected microseismic event (Figure 5.10b). The distance to the furthest detected events could reach 879 m under the injection volume of 74483 m³. For the NS-oriented wells, such a relationship between injection rate and distance to the furthest detected microseismic event was relatively weaker ($R^2 = 0.520$). The distance to the furthest detected events could reach 749 m under the injection volume of 52818 m³. These results can be compared with the prior results that a "respect" distance of 895 m between horizontal boreholes orientated perpendicular to the maximum horizontal stress direction and faults optimally oriented for failure under regional stress field (Wilson et al., 2018).

Overall, the moderate distance (879 m for NS-oriented wells and 749 m for NW-SE-oriented wells) between the new wellbore and the seismogenic fault could mitigate the effects of hydraulic connection between known faults and the stimulated well. Such moderate distance can be determined by the coupled flow-geomechanical modeling via integration of geological, geomechanical and hydrological factors. This practice provides

insights to help industrial managers mitigate seismic hazards by optimizing the site selection of horizontal wells relative to known faults.

Figure 5.10. (a-b) Map view of fracturing horizontal wells and monitored induced seismicity events in selected cases. (c-d) Statistics of distance to the furthest detected microseismic event against the injected fluid volume for the N-S-oriented wells and NW-SE-oriented wells, respectively.

5.2 Insights on controlling factors of hydraulically induced seismicity in the Duvernay East Shale Basin⁴

Abstract

Historically, the Duvernay East Shale Basin had been regarded as a seismicity-quiescent region. However, an ML 4.18-magnitude earthquake on 04/03/2019 was triggered due to the hydraulic fracturing of two horizontal wells. The physical mechanism and controlling factors of this large-magnitude earthquake are not well understood. In this work, the coupled modeling of the ML 4.18 case is conducted to quantify the poroelastic effects during fluid injection and to reveal the triggering mechanism of this earthquake cluster. Additional simulations of tested cases with different hydraulic, geomechanical, and operational parameters are also conducted to quantify the effects of these factors on hydraulically induced seismicity. It is found that the hydraulic fractures of two wells propagated within the Duvernay formation and connected with the inferred fault. The increase in pore pressure reduced the shear stress of the fault and caused the fault slip. The hydraulically induced seismicity is susceptible to the low permeable injection layer and high permeable fault, less rigid fault with low Biot's coefficient, large fluid injection, and proximity of HF-fault distance. Enlarging the distance between the stimulated well and the seismogenic fault is the first-order choice to mitigate seismic risks. Under the proximity of

⁴ Hui, G., Chen, S., Gu, F., et al. (2021d). Insights on controlling factors of hydraulically induced seismicity in the Duvernay East Shale Basin. *Geochemistry, Geophysics, Geosystems*, 22, e2020GC009563. <https://doi.org/10.1029/2020GC009563>

well-fault distance, reducing the fracturing size job would be an effective approach to reduce the expected magnitude of hydraulically induced seismicity.

5.2.1 Introduction

The recent induced seismicity in the Western Canada Sedimentary Basin (WCSB) has been attributed to the industrial operations targeting unconventional hydrocarbons, such as hydraulic fracturing (HF) (Atkinson et al., 2016; Schultz et al., 2018; Van et al., 2017; Schultz et al., 2020). Statistically, 6% of HF operations targeting the Duvernay Formation are related to the induced seismicity with moment magnitude $M_L > 3$ in WCSB (Ghofrani and Atkinson, 2020). The occurrence of some large magnitude HF-induced seismicity in WCSB has been linked to site-specific geological, geomechanical, and operational factors, including the proximity to basement and carbonate reef margins, formation overpressure, shale content and total organic content (TOC), critical stress state of seismogenic faults, the hydraulic connection between pre-existing faults and stimulated wells (Schultz et al., 2017; Pawley et al., 2018; Eaton and Schultz, 2018; Eyre et al., 2019; Zhang et al., 2019; Hui et al., 2021a-2021g). It is noted that the operational factors are aiming to be proxies for whether there are likely to be the necessary conditions present (e.g., specifically, the presence of a critically stressed fault). Since this is not possible to know (many faults not imaged; stress state unknown, etc.), here, we use a variety of proxies as indicators of likelihood. Several triggering mechanisms are proposed to account for the nucleation of HF-induced seismicity, including pore pressure diffusion and poroelastic stress perturbation, remote dynamic, runaway rupture, etc., which can decrease the fault strength and thus cause faults to slip (Ellsworth, 2013; Galloway et al., 2018; Healy et al., 1968; King and Deves, 2015; Atkinson, 2016).

Traditionally, some regions in WCSB have been regarded as seismicity-frequent areas, such as the Fox Creek region. Since 2013, several hydraulically induced seismicity events with $M_L > 3$ have been reported in Fox Creek (Bao and Eaton 2016; Wang et al. 2017; Eaton et al. 2018; Eyre et al. 2019). By contrast, the Duvernay East Shale Basin (ESB), located in the south WCSB, had been regarded as the seismicity-quiescent region until May 2017 (Schultz and Stern, 2015; Schultz and Wang, 2020). Many tectonics-induced seismicity events occurred in the west mountain deformation region based on the Composite Alberta Seismicity Catalogue (Figure 5.11). Very few events were observed in the Red Deer area before March 2019; these were non-tectonic events with $M_L < 2$. However, on 4 March 2019, an M_L 4.18-magnitude earthquake was triggered during fracturing stimulations of two horizontal wells (Schultz and Wang, 2020; Wang et al., 2020). This red-light event (earthquakes with $M_L > 4.0$) was also felt by nearby residents and hence received public concerns for fracturing-induced seismicity. Given the new occurrence of this event and the unavailability of related data, the underlying mechanism of this earthquake has not been well understood. Moreover, the geological, geomechanical, and operational factors that influence this red-light event are also uncertain. However, to date, the availability of datasets including well data, seismicity catalog, and treatment data makes it possible to investigate the underlying mechanism and controlling factors of hydraulically induced seismicity and propose strategies to mitigate future seismic hazards.

In this work, the geological, geomechanical, and operational conditions of M_L 4.18 earthquake clusters are first investigated and determined as the reference case. The coupled fluid flow-geomechanical modeling of this reference case is then conducted to quantify the poroelastic effects during fluid injection and to reveal the trigger mechanism of this red-

light event. Additional simulations with various hydraulic, geomechanical, and operational parameters are also conducted to quantify the effects of these factors on HF-induced seismicity. The operational mitigation strategies are then proposed to reduce future seismic risks in this region.

Figure 5.11. Map view of event hypocenters showing the historical seismicity in Duvernay Eastern Shale Basin (www.inducedseismicity.ca/catalogues, last accessed on 2020/09/01). Red magnitude-scaled circles represented recorded earthquakes from 2011/02/16 to 2020/01/10, with a magnitude range of 0.7 ~4.27. The blue polygon marks the location of Red Deer. Two beachballs show the focal mechanisms of two large magnitude events, and the grey polygon marks the outline of the Duvernay Formation (Schultz and Wang, 2020). The light blue line denotes the trajectory of associated horizontal wells. The colored triangles are regional seismic monitoring stations (Wang et al., 2020).

5.2.2 Datasets

The studied case is located in the middle of ESB, 15 km southwest away from Red Deer (Figure 5.11). Two north-south horizontal wells targeting the Duvernay formation were drilled at ~1770 m below sea level (~2720 m depth below surface) (Figure 5.12a-12d). The hydraulic fracturing operations progressed northward from the toes of both wells on 2019/02/22. As treatments continued, the M_L 4.18 event was triggered on 2019/03/04. The magnitude of this earthquake exceeded the red-light threshold of traffic light protocol, leading to the ceasing of HF operations (Alberta Energy regulator, 2015). By that time, 39 stages of the west well and 38 stages of the east well were completed. The average injection rate of fracturing fluids for both wells is 14.67 m³/min, and the total injection volume reaches 10 866 m³ (Figure 5.12e) (Schultz and Wang, 2020).

The fracturing operations were monitored by the regional seismology networks (red triangles in Figure 5.12a) and 417 induced seismicity were detected (Schultz and Wang, 2020; Wang et al., 2020). In this work, 38 events with the resolved focal mechanisms were selected and shown in Figure 5.12. These events were induced from 2019/02/22 to 2019/04/07 along and away from the east wellbore, with a variety of M_L 0 ~ 4.18. The 417 $M > 0$ events were all induced from the last two stages of two wells, including the 38th - 39th stage of the west well and 37th - 38th stage of the east well (Figure 5.12b and 5.12e). The activated fault planes of the M_L 4.18 event are interpreted with a focal strike of 20°, a dip of 72°, and a rake of -179° (Schultz and Wang, 2020). It is also worth noting that the distribution of some induced events exhibited a NE-SW trending lineament, indicating the possible direction of the inferred fault. In addition, the majority of induced events nucleated within the range of 2.5-3.5km below the surface, consistent with the focal depth of 2.7km

of the $M_L 4.18$ mainshock. The formations with which the events occurred at the Duvernay, Swan Hills and Precambrian Formations. The large magnitude events (blue balls in Figure 5.12c) mainly occurred within the stimulated Duvernay Formation, whereas some small magnitude events (green and yellow balls in Figure 5.12c) concentrated approximately within the focal depth of approximately 2.8km, 300 below the Duvernay Formation. Based on the event magnitude, nucleation time and position of the latter clusters, these events might be the aftershocks of the blue large-magnitude events. The hydraulic, geomechanical, and operational parameters associated with $M_L 4.18$ earthquake swarm are first determined as the input of the reference case. The following sections show the modeling procedures of the reference case.

Figure 5.12. Spatial and temporal view of events and HF treatments. (a-d) Spatial view of event epicenters, colored by time and scaled by magnitude (Wang et al., 2020). The dashed black line in (b) indicates the

lineament distribution of induced events. The fracturing stages (triangles) are colored with the same color-bar as the induced events. The black circles denote the location of vertical wells with available core analysis data. (e) Daily observation of induced events and injection volume per stage (Schultz and Wang, 2020). The gray vertical line represented injection volume per stage (10^3m^3). All induced events are triggered after the 37th stage (east well) and 37th stage (west well) completion.

5.2.3 Coupled fluid flow-geomechanics modeling

(1) Characterization of the inferred fault and hydraulic fractures network

The spatial distribution of induced seismicity exhibits a NE-SW trending lineament (Figure 5.12b), indicating the possible direction of the inferred fault. Besides, the resolved focal strike of the inferred fault is interpreted as NE20° and NW70° (Schultz and Wang, 2020). Therefore, NE20° is adopted as the fault strike used in this work. Furthermore, the actual fault in the crust is a discontinuous interface dominated by frictional constitutive relations. In this study, a continuous fault zone is used as an approximation. Prior works suggested that the spatial distribution of induced events (x, y coordinates) could define the possible length and width of inferred faults, corroborated by the 3D seismic interpretation results (Hui et al., 2021c). Therefore, the possible length and width of the inferred fault, in this case, are estimated to be approximately 900m and 520m, respectively. The thickness of fault is assigned to the empirical value, 5m-core surrounded by 20m-damage-zone on each side (Yehya et al., 2018; Fan et al., 2019). The spatial distribution of the inferred fault is shown in Figure 5.13. The uncertainty of fault geometry parameters will be discussed in Section 5.2.5.

Given that the hydraulic fracture length is larger than fracture height under the strike-slip stress regime in WCSB (Hui et al., 2021e), the Perkins-Kern-Nordgren (PKN)

model is adopted to estimate the geometry of hydraulic fractures (Yew and Weng, 1997). The leak-offs of fracturing fluids towards the matrix are neglected owing to the low permeability ($1.79 \times 10^{-20} \text{ m}^2$) of the shale-hosted Duvernay Formation. Under the assumption of the elliptical cross-sections and fixed height, the fracture length and width at a given time are computed using the following expressions (Yew and Weng, 1997):

$$L(t) = 0.68 \left[\frac{Gq_0^3}{(1-PR)\mu h^4} \right]^{1/5} t^{4/5}, \quad (6-1)$$

$$W(t) = 2.5 \left[\frac{(1-PR)\mu q_0^2}{Gh} \right]^{1/5} t^{1/5}, \quad (6-2)$$

$$P_w(t) = 2.5 \left[\frac{G^6 \mu q_0^2}{(1-PR)^4 h^6} \right]^{1/5} t^{1/5}, \quad (6-3)$$

where $L(t)$ is the fracture half-length, m; $W(t)$ is the fracture width, m; $P_w(t)$ is the wellbore pressure at the perforation site, MPa, G is the shear modulus, MPa; q_0 is the pumped fluid rate for each stage, m^3/s ; PR is the Poisson's ratio; μ is the viscosity of the pumped fluid, $\text{Pa}\cdot\text{s}$; h is the fracture height, m; t is the given time, s. $P_w(t)$ will be used as the geomechanical load for each fracturing stage in the coupled model. The shear modulus G is calculated to be 22.5 GPa using the expression $G=YM/2/(1+PR)$, where YM is Young's modulus, GPa. The fracture height is assigned to 42 m, in line with the thickness of the regional Duvernay Formation. The fluid viscosity is 0.04 $\text{Pa}\cdot\text{s}$ based on the treatment data.

Figure 5.13 shows the 3D view of the propagation of hydraulic fractures for both wells. The fracture length of two wells covers the range of 156 ~ 354 m, with an average value of 248 m. The fracture width is averaged to be 0.0269 cm with a range of 0.0225 ~ 0.0321 cm. The wellbore pressure of both wells has a range of 5.85 ~ 8.34 MPa, with an average value of 6.99 MPa. This wellbore pressure for each stage would function as the

injection source in the following coupled simulation. The hydraulic fractures propagated along with the maximum principal stress, connecting the inferred fault and generating the fracture and fault networks. The fault networks pose an essential role in fault activation during HF operations.

Figure 5.13. 3D view of the inferred fault and hydraulic fracture networks. The fault geometry is determined by the spatial distribution of induced events. Hydraulic fractures are propagated along S_{Hmax} and connected with the inferred fault. The fault is colored by the fault elevation below the sea level. The inset map shows the 2D view of the networks.

(2) Determination of hydraulic and geomechanical properties and in-situ stress regime

The core analysis results of the nearby vertical wells (black circles in Figure 5.12) are utilized to estimate the hydraulic properties of the Duvernay Formation. Figure 5.14a

shows the distribution of porosity and permeability of these key wells, giving the average value of 0.055 ± 0.005 and $1.79 \pm 0.18 \times 10^{-20} \text{ m}^2$ for the porosity and permeability, respectively. The measured total organic content (TOC) of other key wells (well 05-18, 14-06, and 08-20) is averaged to be $2.64 \pm 0.3\%$, lower than that in the Fox Creek area, indicating less susceptibility of fault stability in terms of low TOC content (Eyre et al., 2019). The average formation density of $2671 \pm 250 \text{ kg/m}^3$ is obtained from the available logging data of nearby wells (Hui et al., 2021c). The geomechanical properties such as Young's modulus ($Y_M = 55 \pm 5 \text{ GPa}$) and Poisson's ratio ($PR = 0.25 \pm 0.02$) are derived from the available velocity logging data of nearby wells (Ronald et al., 2019).

Figure 5.14b shows the nucleation position of fault activation for an optimally fault in the normal, reverse, and strike-slip regimes with a conduit-barrier, sealing, and conduit fault permeability structure (Fan et al., 2019). It is noted that under the strike-slip stressing regime and sealing fault condition, the induced events nucleated within the stimulated layer. Given that the nucleation position, in this case, is concentrated in proximity to the stimulated layer, the seismogenic fault is determined to be a barrier one (Figure 5.14b). The barrier fault refers to a fault in which the fluid diffuses relatively slowly. The empirical hydraulic and geomechanical properties of a barrier fault are used in this case. Specifically, the fault porosity, permeability, and density are assigned to 0.01, $1 \times 10^{-17} \text{ m}^2$, and 2500 kg/m^3 , respectively (Yehya et al., 2018). Similarly, the Biot's coefficient (α) of fault, used to quantify the efficiency of fluid diffusion in response to the applied stress, is assumed to be 0.44 owing to low fault permeability (Fan et al., 2016). The Young's modulus and Poisson's ratio of fault are set with 10 GPa and 0.15, respectively, consistent with the elastic

properties of low-permeability fault (Haddad et al., 2020). These fault properties will be incorporated into the following coupled model.

Figure 5.14. (a) Relationship between porosity and permeability of core samples in the ESB region. (b) The nucleation position of fault activation for an optimally fault in the normal, reverse, and strike-slip regimes with a conduit-barrier, sealing, and conduit fault permeability structure (Fan et al., 2019). The letter A or A' shows the fault activation within the stimulated formation, whereas B or B' denotes the fault activation in the basement. The magenta rectangle marks the conditions in the studied case.

The full stress tensors in the ESB region are also determined based on the logging and treatment data. The direction of maximum principal stress S_{Hmax} is employed as NE47°, consistent with the nearby measured value in the World Stress Map and prior works (Reiter et al., 2014; Shen et al., 2019). Therefore, the β , as the angle of fault strike (NE20° in this case) relative to S_{Hmax} , is assigned to the value of 27. The density logs of nearby vertical wells are utilized to calculate the gradient of vertical stress ($\partial S_v / \partial z$) to be 17.5 ± 0.17 kPa/m (Zoback, 2007). The pore pressure gradient ($\partial P_p / \partial z$) is estimated to be 13.8 kPa/m based on prior works (Shen et al., 2019; Eaton and Schultz, 2018). The gradient of minimum principal stress ($\partial S_{min} / \partial z$) is evaluated to be 15.8 ± 1.08 kPa/m from the previous contour map (Pawley et al., 2018). Based on the empirical expression: $S_{Hmax} = 3S_{hmin} - 2P_p$ (Zoback, 2007), the gradient of S_{Hmax} was calculated to be 19.8 kPa/m with an uncertainty interval of -2.37 to +2.37 kPa/m. Therefore, the faulting stress regime in the studied region is regarded as the strike-slip mechanism ($S_{Hmax} \geq S_v \geq S_{hmin}$) (Zoback, 2007). In this strike-slip mechanism, the barrier properties of faults (sealing fault) account for their nucleation position proximity to the stimulated formation (Figure 5.14b) (Fan et al., 2019).

According to the above stress tensors and the focal depth of the induced events, the Mohr diagram is plotted to depict the initial stress state of the source mechanisms prior to fracturing stimulations (Figure 5.15). The calculation of the effective normal stress and shear stress is well documented in prior works (Hui et al., 2021b). A value of 0.6 for the friction coefficient is adopted under the assumption of a critically stressed state of the inferred fault. The dashed line shows the computed fluid pressure that is required to reduce the effective normal stress on the fault plane and cause the fault slip. Therefore, the

effective stress state of the induced events related to the inferred faults is shown in Figure 5.15, with color consistent with their nucleation time (inset map in Figure 5.15). It is worth noting that the northeast-trending fault plane (blue line in the beachball) of the M_L 4.18 earthquake is optimally oriented for slip. Similarly, a subsequent event illustrates the same pattern as the red-light event (green ball in Figure 5.15). Thus, an increase in pore pressure of only 0.5 MPa is required to activate this fault during and after HF operations. This critical value will be used in the coupled modeling to determine the activation of this inferred fault.

Figure 5.15. Mohr diagram plotted using the calculated effective stresses before HF operations. A value of 0.6 for friction coefficient is adopted under the assumption of a critically stressed state of the fault. The induced events related to the inferred faults are marked by circles, colored by nucleation time. The dashed black line depicts the calculated increase pressure required to cause the fault slip. The short black lines in the x-axis denote the errors in stress calculation. The right map shows the 2D view of related events and focal mechanisms.

(3) Coupled poroelastic modeling and results

Table 5.2 shows the hydraulic, geomechanical, and operational parameters for the reference case. The finite element method is utilized with triangular elements to characterize the spatiotemporal changes of poroelastic stress and pore pressure during fracturing stimulations. The block model covers the dimension $4000 \text{ m} \times 4500 \text{ m} \times 500 \text{ m}$ (x, y, and z-axis). The Duvernay, Swan Hills, Cambrian and Precambrian Formations are set with a thickness of 40, 110, 120, 230 m, respectively, generating the multi-layer system in the model. One inferred fault, two horizontal wells, and 77 stages of hydraulic fractures are all introduced into the model (Figure 5.16a). The triangular elements are processed to compute the element volumes and geometric transmissibility, with a refined mesh within or surrounding the fault and hydraulic fractures (Figure 5.16b). A fixed boundary (zero-flow rate) is set in the model. The top surface is set to traction-free while the displacement at the lateral boundaries and the bottom surface is set to be zero (Fan et al., 2019). The fluid system is assumed to be in an initial state of hydrostatic equilibrium. The wellbore pressure per stage, calculated by equation (3), is regarded as the injection source over time. The hydraulic, geomechanical, and operational parameters of formations, faults, and fluids in the reference case are also introduced into the model (Table 5.2).

Table 5.2. Hydraulic, geomechanical, and operational parameters used in the coupled model as the reference case

Factors	Parameters	Formation	Fault	Fluid	Description
Hydraulic	$k \text{ (m}^2\text{)}$	1.79×10^{-20}	1×10^{-17}	—	Permeability
	Φ	0.055	0.01	—	Porosity
	$\rho \text{ (kg/m}^3\text{)}$	2671	2500	1000	Density
	$\eta \text{ (Pa.s)}$	—	—	0.4×10^{-3}	Viscosity

Geomechanics	E (GPa)	55	10	—	Young's modulus
	ν	0.25	0.15	—	Poisson's ratio
	G (GPa)	22	4.3	—	Shear modulus
	α	0.44	0.44	—	Biot's coefficient
	$\partial P_p / \partial z$ (kPa/m)	13.8		—	P_p gradient
	$\partial S_{Hmax} / \partial z$ (kPa/m)	19.8		—	S_{Hmax} gradient
	$\partial S_{hmin} / \partial z$ (kPa/m)	15.8		—	S_{hmin} gradient
	$\partial S_v / \partial z$ (kPa/m)	17.5		—	S_v gradient
	β (°)	—	27	—	Fault- S_{Hmax} angle
Operational	q (m ³ /min)	—	—	14.67	Injection rate
	V _{injection} (10 ⁴ m ³)	—	—	10.87	Injection volume
	d _{fault-HF} (m)	—	-100	—	HF-fault distance

Figure 5.16. Initialization of coupled model. (a) The horizontal wells, hydraulic fractures, inferred fault, and formations are embedded in the block model. (b) The triangular elements mesh is defined with refinement proximity to the fault and hydraulic fractures.

Figures 5.17a-17c show the horizontal cross-section view of simulated pore pressure changes (ΔP_p) at the nucleation position (magenta cross) along with different stage completions. It is shown that ΔP_p at the nucleation position remains zero before the 26th stage completion of the east well and the 29th stage completion of the west well due to the low diffusivity of shale matrix and no hydraulic connection with inferred faults. Subsequently, the 26th-31st stage of the east well and the 29th stage of the west well propagated along NE47° and connected with the inferred fault. Under the HF-fault hydraulic connection, the fracturing fluids could propagate through hydraulic fractures into the inferred fault, enlarging the pore pressure of the fault zones (Tan et al., 2020). A slight increase in ΔCFS , $\mu\Delta P_p$, $\mu\Delta\sigma_n + \Delta\tau$ is observed before 04/03/2019 (Figure 5.17d), as the pressure front didn't arrive at the nucleation position (Figure 5.17b). As the 38th stage of the east well and the 39th stage of the west well were fractured, the pressure front reached

the nucleation position, leading to a sharp increase in stress and pressure surrounding the fault zone (Figure 5.17c). The corresponding maximum ΔCFS , $\mu\Delta P_p$, $\mu\Delta\sigma_n + \Delta\tau$ at the nucleation position and time reached 2.4, 1.9, and 0.5 MPa, respectively, sufficient to overcome the strength of fault and cause the fault slip (Figure 5.15). Therefore, stage completions prior to the 26th stage completion of the east well and the 29th stage had nearly no contributions to elevated pore pressure that caused the fault slip. Instead, the 26th -37th stage of the east well and the 29th -39th stage of the west well significantly increased the pore pressure and triggered the induced events. It is worth noting that the elevated pore pressure within the fault zone is the predominant factor that activated the seismogenic fault in this case (Galloway et al., 2018).

Figure 5.17. The simulated results of coupled modeling in the reference case. (a-c) Horizontal cross-section view of ΔP_p at the nucleation position along with different stage completions. (d) Temporal ΔCFS , $\mu\Delta P_p$, $\mu\Delta\sigma_n+\Delta\tau$ at the cross point in the Duvernay formation.

5.2.4 Sensitivity analysis of hydraulic, geomechanical, and operational properties

(1) Determination of tested controlling parameters

A series of sensitivity tests are performed to quantify the effect of hydraulic, geomechanical, and operational parameters in terms of ΔCFS on fault activation during

hydraulic fracturing operations. The varied hydraulic, geomechanical, and operational properties for tested cases are selected based on their importance in prior works (Table 5.3) (Pawley et al., 2018; Schultz et al., 2018; Fan et al., 2019). Specifically, the role of permeability of the injection layer (Case 2) and seismogenic fault (Case 3) on fault activation is investigated to understand the effect of varied hydraulic properties on pressure diffusion during hydraulic fracturing. Furthermore, the different shear modulus of fault (G_{fault}) (Case 4) and Biot's coefficient (α) (Case 5) are studied to characterize the poroelastic effect that responded to fluids injection. The different injection rate (q) of fracturing fluid (Case 6), which also represents the injection volume, and the varied distance between the hydraulic fractures and inferred fault ($d_{\text{fault-HF}}$) are quantitatively compared to depict the operational factors that influenced the fault activation. To better quantify the effect of these parameters on ΔCFS , as shown in Table 5.3, the low values of geomechanical and operational parameters are assigned to 50% of the reference value, 100% for the medium value, and 150% for the high value. The low and high values of fault and formation permeability (hydraulic parameter) are set with 1/10 and 10 times of reference value in order to obtain a comparable result. Similarly, the $d_{\text{fault-HF}}$ are assigned to -100, 0 (HF just connect with the fault), and 100 m, respectively.

We use the Coulomb failure criterion to determine the ΔCFS on fault activation in tested cases. The ΔCFS , in terms of pore pressure, normal and shear stresses on the fault, is calculated by (Zoback 2007)

$$\Delta\text{CFS} = (\Delta\tau + \mu\Delta\sigma_n) + \mu\Delta p_p, \quad (6-4)$$

where Δ denotes the changes in each parameter; CFS is the Coulomb failure stress; τ is the shear stress (positive in the slipping direction); σ_n is the normal stress (positive in the extensional direction); μ is the friction coefficient.

(2) Sensitivity analysis

The coupled poroelastic simulations for six tested cases are then conducted to quantify the effects of hydraulic, geomechanical, and operational factors on HF-induced seismicity. Figure 5.18a shows the simulated temporal at the cross point (blue cross in Figure 5.17a) with different injection layer permeability. It is found that a low-pressure diffusion in the tight layer ($k_{\text{injection}}=1.79 \times 10^{-22} \text{ m}^2$) cumulates to a relatively higher value of ΔCFS . On the contrary, the high-permeability stimulation layer ($k_{\text{injection}}=1.79 \times 10^{-18} \text{ m}^2$) favors a rapid pore pressure-diffusion but ends with a relatively low value of ΔCFS (Figure 5.18a). However, the difference of ΔCFS that are responded to different injection permeability is not remarkable. By contrast, the fault permeability illustrates a different scenario (Figure 5.18b). The high-permeability fault ($k_{\text{fault}}=1 \times 10^{-15} \text{ m}^2$) allows rapid pressure diffusion surrounding the fault, thus leading to a relatively low ΔCFS value of 1.2 MPa. However, a barrier fault ($k_{\text{fault}}=1 \times 10^{-19} \text{ m}^2$) would not favor the rapid pressure diffusion, and hence the maximum ΔCFS could cumulate to a relatively high value of 2.88 MPa. The ΔCFS in response to fault permeability is relatively remarkable in comparison with injection layer permeability.

The rigidity of fault in terms of shear modulus (G) also poses an effect on the shear stress of fault. Biot's coefficient (α) refers to the efficiency of pore fluid in response to applied stress (Fan et al., 2016). It is found that a more rigid fault ($G=6.52 \text{ GPa}$ in Figure 5.18c) with a high Biot's coefficient ($\alpha=0.66$ in Figure 5.18d) requires more poroelastic

energy to activate. For operational factors, the corresponding maximum ΔCFS is proportional to the injection rate of fracturing fluid (Figure 5.18e), demonstrating that the injection rate and volume is the essential factor that influences fault activation during hydraulic fracturing. Another important factor is the distance between the hydraulic fractures and inferred faults. When the distance is set with -100, 0, and 100 m, the associated maximum ΔCFS was 2.40, 2.18, and 0.30 MPa, respectively, indicating that the fault-HF distance is also a crucial factor that causes the fault slip (Figure 5.18f).

According to the simulation results of the reference case and tested cases, the high permeable fault, large fluid injection rate and HF-fault distance are more important in contributing to ΔCFS at the nucleation position and time. Meanwhile, the low permeable injection layer and the rigidity of fault with low Biot's coefficient are relatively less important (Figure 5.18a-18f). The tornado plots are then mapped to rank the role of these parameters on fault activation (Figure 5.18g). Specifically, by comparing the ΔCFS at the nucleation position and time under low, medium and high values of each factor, we can evaluate its effect on ΔCFS (Figure 5.18f). For example, the blue horizontal bar of injection rate in Figure 5.18g shows that the ΔCFS with low injection value is approximately 70% of the reference value, whereas the brown one indicates that the ΔCFS with high injection value reaches approximately 138% of the reference value. This result indicates the significance of injection volume on the ΔCFS . Therefore, the controlling factors of hydraulically induced seismicity are listed in the order of decreasing importance by HF-fault distance, fault permeability, injection rate, fault rigidity, injection layer permeability, and Biot's coefficient. The role rank of these factors could provide insights into the mitigation strategy for industrial companies to mitigate the risks of future seismic hazards.

Table 5.3. Varied hydraulic, geomechanical, and operational properties for tested cases

	Parameters	Unit	Low	Medium	High
Hydraulic	$k_{\text{injection}}$	(m ²)	1.79×10^{-22}	1.79×10^{-20}	1.79×10^{-18}
	k_{fault}	(m ²)	1×10^{-18}	1×10^{-17}	1×10^{-16}
Mechanics	G_{fault}	(GPa)	2.15	4.3	6.45
	α_{fault}		0.22	0.44	0.66
Operational	q	(m ³ /min)	7.33	14.67	22.0
	$d_{\text{fault-HF}}$	(m)	-100	0	100

Figure 5.18. Sensitivity tests for hydraulic, geomechanical, and operational factors. (a-f) Simulation results of six tested cases at the nucleation position and time in terms of injection layer permeability, fault permeability, fault rigidity, Biot's coefficient, injection volume, and HF-fault distance. (g) Tornado plots for hydraulic, geomechanical, and operational factors. The x-axis shows the ratio of ΔCFS the under low, medium and high values of each factor to the reference value.

5.2.5 Discussion

(1) Mitigation strategy

Based on the quantification of poroelastic effects in terms of hydraulic, geomechanical, and operational factors on HF-induced seismicity, the mitigation strategy is proposed accordingly to reduce the potential seismic hazards in ESB. Figure 5.18g shows the important role of HF-fault distance, injection rate, and fault permeability on fault activation. The high permeability of the fault would facilitate the pressure diffusion downwards or upwards with the fault hence unlikely to cumulate to a high value at a depth of the injection site. However, for regions with site-specific geology and geomechanical parameters, we cannot change the fault permeability but could perform the operational controls such as reducing injection rate and enlarging HF-fault distance to mitigate seismic hazards. Prior works showed the applicability of operational controls on risk mitigation (Schultz et al., 2018; Hui et al., 2021e). Enlarging the distance between the stimulated well and the seismogenic fault is the most effective approach in the studied case based on the simulation results (Figure 5.18g), which mitigates the HF-fault hydraulic communication during and after stimulations. However, this strategy depends largely on the identification of pre-existing faults prior to HF operations. The available 3D seismic reflection data is

required to cover the area of interest, and the ant-tracking approach is required to identify the nearby small offset fault (Hui et al., 2021b). Nevertheless, it is worth noting that not all pre-existing faults associated with induced seismicity can be successfully identified in advance, even with the 3D reflective seismic data. In scenarios that horizontal wells have been drilled with short well-fault distance, reducing the fracturing job size (e.g., decreasing injection rate, volume) would be another effective approach to reduce the magnitude of hydraulically induced seismicity (Figure 5.18g). However, in this case, reducing the injection rate means a decrease in stimulation reservoir volume (SRV), which would pose a negative effect on the hydrocarbon production performance (Wang et al., 2019). This situation should be comprehensively investigated and strike a balance between seismicity mitigation and production performance. Additionally, some operators use the particular viscosity of fracturing fluids as a potential mitigation strategy (e.g., fracturing with different fluids in stages connected to a fault). We performed the coupled modeling with different viscosity of fracturing fluids. The results suggested that the ΔCFS at the nucleation position and time reduces by 50% if the viscosity of the fluid is 100 times (400 mPa.s) larger than the original one (0.4 mPa.s). This effect can be explained that the fluid with a large fluid viscosity diffuses slowly within the fault zone, which possibly reduces the ΔCFS and hence mitigates the seismic risks. However, this strategy needs more field cases to verify and quantify the effect of high viscosity fluid on risks mitigation. Overall, enlarging the HF-fault distance and reducing the fracturing job size could mitigate the potential seismicity risks.

(2) Aftershocks investigation

When a seismogenic fault slips, the surrounding rocks will deform elastically, and the ambient stress regime will be rearranged. This physical process will induce a region with a positive or negative ΔCFS in proximity to the fault. In regions with positive ΔCFS , the fault may reach a less stable state and thus lead to the subsequent slippage on nearby faults (Stiros and Kontogianni, 2009). The Coulomb failure criterion shows the effective application in forecasting the aftershocks (Catalli et al., 2013). The Coulomb 3.3 software program is used in this work to compute ΔCFS surrounding the inferred fault after the M_L 4.18 mainshock event (Toda et al., 2011). The inferred fault, in-situ stress and other geological properties in the Coulomb 3.3 are set the same parameters as in the FEM model. First, the inferred fault in this work is assigned as the fault that receives the Coulomb failure stress triggered by the M_L 4.18 mainshock. The activated fault plane with a focal strike of 20° , a dip of 72° , and a rake of -179° (Schultz and Wang, 2020) are introduced into the software program. Then the effective friction coefficient is set with the empirical value of 0.4 (Zhao, 2018). The displacement of the inferred fault is assumed to be uniformly distributed. Figure 5.19 shows the simulated spatial ΔCFS at a depth of 1.9 km (average depth of subsequent events) after the M_L 4.18 mainshock. It is found that only one event with a magnitude of 0.42 that occurred on 07/04/2019 (red cycle) is located within the positive region (red color), whereas the other events concentrate within the negative region (blue color). Therefore, only the M_L 0.42 event was the aftershock following the M_L 4.18 mainshock. The other events might be induced by the pressure diffusion of fracturing fluid within the low permeability fault zones (Figure 5.13). Therefore, two types of triggering mechanisms account for the occurrence of subsequent clusters after 11/03/2019. These results are consistent with prior works in the case of ESB (Wang et al., 2020).

Figure 5.19. ΔCFS at a depth of 1.9 km (average depth of subsequent events) after the M_L 4.18 mainshock. The inset map shows the nucleation time of the induced events. Two types of triggering mechanisms account for the occurrence of subsequent clusters after 11/03/2019.

(3) Uncertainty analysis

Generally, the resolved focal mechanism of induced seismicity exhibits relatively small misfits, which indicates the uncertainty of event hypocenters (Zhang et al., 2019). For example, the event epicenter location in ToC2ME covers the errors of ± 30 m laterally and ± 70 m in depth (Eaton et al., 2018). This uncertainty in event hypocenters would pose a negative effect on the simulation work, such as the uncertainty in the fault size and spatial distribution. In this scenario, the available 3D seismic reflection data could facilitate

determining the relatively reliable location of the inferred fault (Hui et al., 2021e). In addition, the in-situ stress tensors and pore pressure are derived from the treatment and logging data, which also have uncertainty in the stress and pressure estimation. As shown in Figure 5.15, the short black lines in the x-axis denote the errors in stress and pressure calculation. The PKN model is adopted in this work to simplify the propagation of hydraulic fractures. Each hydraulic fracture propagates along with the maximum principal stress, whose lengths are calculated by Equation (2). However, in the actual case, the regional stress field surrounding hydraulic fractures will rearrange due to fracturing operations. Some natural fractures in proximity to the wellbore will be activated and connected with the propagated hydraulic fractures, thus generating a natural fracture and hydraulic fracture network (Yew and Weng, 1997). The characterization of this network could be accomplished by the comprehensive analysis of high-resolution 3D seismic interpretation, net pressure history-matching of each stage, and fine microseismicity monitoring work. In addition, the PKN model used in this work does not consider the interaction between multiple propagating fractures. The effect of such interaction on the coupled modeling results needs to be investigated in future studies.

Furthermore, based on the statistics of Figure 5.14a, the permeability of the injection layer has a range of $1.34 \times 10^{-21} \sim 1.50 \times 10^{-19} \text{ m}^2$. In the reference case, the average value of $1.50 \times 10^{-19} \text{ m}^2$ is adopted as the permeability of the injection layer, the error of which would pose a negative effect on the coupled modeling results. In this work, the leak-off effect is neglected in the PKN model and coupled simulation. If the leak-off effect is considered in the coupled modeling and simulation, the ΔCFS surrounding the hydraulic fractures will move into the shale matrix, which possibly reduces the cumulated ΔCFS

during and after HF operations and mitigate the seismic risks. The quantification of this effect needs more available leak-off data and corresponding coupled modeling and simulation. In the coupled modeling, the boundary conditions have an impact on the modeling results. We perform a new model with a boundary of $8000\text{ m} \times 9000\text{ m} \times 500\text{ m}$ (x, y, and z-axis), in comparison with the original case of $4000\text{ m} \times 4500\text{ m} \times 500\text{ m}$. The modeling results show that the new ΔCFS at the nucleation position of $M_L 4.18$ event is 92% of that of the original case. Therefore, in this study, the boundary conditions have a trivial impact on the modeling results. In discerning the amount of ΔCFS required to reactivate the fault, we determine the 0.5 MPa as the critical value based on the friction equilibrium for the $S_{H\text{max}}$ via the Mohr circle. However, in reality, this estimation is just an upper bound of $S_{H\text{max}}$. Some factors might influence this critical value, including the critical stress state of fault, regional deformation of stress regime and uncertainties of pore pressure and $S_{H\text{max}}$. The quantification of this effect needs to be investigated in future studies. Moreover, in the FEM model, the elevated pore pressure responded to HF operations exceeded 0.5 MPa and caused the fault to slip, which verifies the robustness of FEM model. The further validation of the FEM model needs to be investigated in future studies.

5.3 Summary

We explore the controlling factors of hydraulic fracturing-induced seismicity based on the $M_w 3.0$ case and $M_L 4.18$ case in Western Canada. The $M_w 3.0$ case near Fox Creek is investigated to quantify the effect of a hydrological connection between stimulated wells and associated seismogenic faults on hydraulic fracturing-induced seismicity. The poroelastic modeling of the $M_L 4.18$ case is conducted to quantify the effects of different

hydraulic, geomechanical, and operational parameters on hydraulically induced seismicity.

The following conclusions are drawn from two cases study.

- (1) The M_w 3.2 induced seismicity was triggered by fluid diffusion through hydraulic fractures along high-permeability fault damage zones downwards into the basement. This basal fault slip was attributed primarily to the elevated pore pressure along the fault plane in response to fracturing fluid injection.
- (2) The moderate distance (879 m for NS-oriented wells and 749 m for NW-SE-oriented wells) between the future horizontal wellbores and critically-stressed fault could mitigate the effects of well-fault hydraulic connection and thus reduce the seismicity risks. The proper real-time monitoring with downhole and/or surface microseismicity is required to perform to avoid unwanted seismicity hazards during and after HF operations in the WCSB.
- (3) The M_L 4.18 earthquake clusters were triggered by the hydraulic connection between stimulated wells and inferred fault. The elevated pore pressure is also the predominant factor that activated the seismogenic fault and triggered the induced seismicity.
- (4) The controlling factors of hydraulically induced seismicity are listed in the order of decreasing importance by HF-fault distance, fault permeability, injection rate, fault rigidity, injection layer permeability, and Biot's coefficient.
- (5) Enlarging the distance between the stimulated well and the related fault is the first-order choice to mitigate seismic risks. Under the proximity of well-fault distance, reducing the fracturing size job would be an effective approach to reduce the magnitude of hydraulically induced seismicity.

CHAPTER 6 COMPREHENSIVE CHARACTERIZATION AND MITIGATION OF HYDRAULIC FRACTURING-INDUCED SEISMICITY⁵

Abstract

It remains unclear about relationships among formation properties, fracturing operations and induced seismicity nucleated at distinctive moments and positions. In this study, a complete dataset on formations, seismicity, and fracturing treatments is collected in Fox Creek, Alberta. Such a dataset is then used to characterize the induced seismicity and evaluate its susceptibility towards fracturing stimulations via integration of geology, geomechanics and hydrology. Five mechanisms are identified to account for spatiotemporal activation of the nearby faults in Fox Creek, where all major events ($M_w > 2.5$) are caused by the increase in pore pressure and poroelastic stress during the fracturing operation. In addition, an integrated geological index and a combined geomechanical index are first proposed to indicate seismicity susceptibility, which is consistent with the spatial distribution of induced seismicity. Finally, mitigation strategy results suggest that enlarging a hydraulic fracture-fault distance and decreasing a fracturing job size can reduce the risks of potential seismic activities.

⁵ Hui, G., Chen, S., Chen, Z., et al. (2021b). Comprehensive characterization and mitigation of hydraulic fracturing-induced seismicity in Fox Creek, Alberta. *SPE Journal*. 26 (05): 2736–2747. <https://doi.org/10.2118/206713-PA>

6.1 Introduction

The recent surging induced seismicity events have been attributed to the anthropogenic resource exploration and production activities, such as hydraulic fracturing, wastewater disposal, and geothermal stimulation (Grigoli et al., 2017; Schultz et al., 2020; Schultz et al., 2014; Wetmiller et al., 1986; Gaucher et al., 2015). Several earthquakes with large magnitudes have been reported in North America, Southern China, the United Kingdom, and Switzerland, which are spatiotemporally correlated with hydraulic fracturing (HF) operations in unconventional resources (Schultz et al., 2020; Lei et al., 2017; Bao and Eaton, 2016; Eyre et al., 2019). During HF operations, tens of thousands of cubic meters of fluids are injected under high pressure to create the tensile failure of low-permeability reservoir rocks and generate fracture networks. Propagation of such hydraulic fractures is generally accompanied by discontinuous and instantaneous low magnitude microseismic events with a moment magnitude (M_w) less than 0, and only 0.8% of fracturing wells are associated with $M_w > 3$ earthquakes in Western Canada (Ghofrani and Atkinson, 2020). However, the Duvernay Formation in the Fox Creek region has witnessed considerable HF-induced seismicity with $M_w > 2.5$ (Figure 6.1). Thus, a comprehensive study is required to understand the triggering mechanisms and mitigate potential seismicity risks.

Two major hypotheses have been proposed to understand the fundamental mechanisms of HF-induced seismicity, including pore pressure diffusion and poroelastic stress perturbation, which can decrease the fault strength and thus cause faults to slip (Ellsworth, 2013; Galloway et al., 2018; Healy et al., 1968; King and Deves, 2015). The pore pressure diffusion is regarded as the primary mechanism for HF-induced seismicity,

which is controlled by the hydrological communication between wells and faults. The second mechanism is the fault slip caused by the poroelastic stress transfer during fracturing fluid injection, which can transmit farther away from a stimulated well. Understanding of both mechanisms needs a comprehensive analysis of fault, hydraulic fractures and formations to explain and thus predict spatiotemporal seismicity patterns, such as the rate, distribution, and magnitude of seismicity (Schultz et al., 2020). For example, an $M_w=3.2$ earthquake occurred in Fox Creek during fracturing treatments, while another $M_w=3.6$ event and an $M_w=4.1$ red-light event were induced several days after fracturing stimulations (Bao and Eaton, 2016; Eyre et al., 2019, Eaton et al., 2018). In addition, the former one was triggered in the injection layer while the latter two were nucleated above and below the injection layers, respectively. Recently, many scholars have conducted researches to investigate the underlying physical mechanisms of induced seismicity. Bao and Eaton (2016) demonstrated that poroelastic stress changes during operations could activate fault slip to a large offset distance, whereas pressurization by hydraulic fracturing into a fault yields episodic seismicity that can persist for months. Lele (2017) claimed that the earthquake was triggered by the direct connection between the nearby faults and hydraulic fractures via the coupled geomechanical model. Eyre (2019) developed an alternative model based on recent laboratory and in situ experiments, wherein distal and unstable regions of a fault are progressively loaded by aseismic slip on proximal and stable regions stimulated by hydraulic fracturing. However, despite the recent progress in seismological or geomechanical modeling to characterize HF-induced seismicity, the underlying physical mechanisms controlled by geological, geomechanical and hydrological factors are not well understood. Thus, it is essential to quantify the effects of

these factors on spatiotemporal nucleations of HF-induced seismicity to mitigate future seismic risks.

In this work, an integrated approach combining geology, geomechanics and hydrology is utilized to characterize HF-induced seismicity based on a comprehensive analysis of Fox Creek datasets. Specifically, the ant-tracking approach is first employed to identify related small-offsets faults that are corroborated by focal mechanisms of mainshocks. An integrated geological index is then proposed to account for the regional geological susceptibility of induced seismicity. A combined geomechanical index is next introduced to assess the geomechanical bias of induced seismicity in the target formations. Coupled hydrology-geomechanics simulations are conducted to quantify poroelastic effects on the fault activation during and after fracturing stimulation. The triggering mechanisms of HF-induced seismicity in various cases are finally determined based on the Mohr-Coulomb failure criterion, accounting for a variety in nucleation time and position. This approach will advance the quantitative understanding of how geological, geomechanical and hydrological factors affect the hydraulically induced seismicity and determine the triggering mechanisms of distinctive induced events. The mitigation measures of enlarging an HF-fault distance and reducing a fracturing job size are evaluated in mitigating risks of potential seismic activities.

Figure 7.1. Map view of recorded seismicity in Western Canada. It shows the historical seismicity of $M_w \geq 2.5$ up to 2020/01/31 from the Composite Alberta Seismicity Catalogue. Red cycles denoted earthquake clusters. The magnitude-scaled beach balls show focal mechanisms of HF-induced (red), tectonic-related (green), and EOR-induced (blue) events (Schultz et al., 2017; Wang et al., 2018). The blue dashed line indicates the estimated deformation edge of the Rocky Mountains. The inset map shows the location of the studied region. The blue polygon marks the extent of induced seismicity. HRB = Horn River Basin; FC = Fox Creek; Br = Brazeau River; RMH = Rocky Mountain House.

6.2 Methods

6.2.1 Seismogenic faults interpretation and fault architecture

The 3D reflection seismic data is utilized to explore the possible linkage between induced seismicity and pre-existing faults (Galloway et al., 2018). Specifically, a synthetic seismogram tie for key wells is first established to pick the related horizons in the seismic reflection survey. The related faults are then identified by tracing small-scale structural discontinuities or offsets via the ant-tracking approach. As an effective approach, ant-tracking employs four procedures to identify small-scale faults, including seismic conditioning, edge detection, edge enhancement, and auto-track interpretation (Pedersen et al., 2002). In this work, the available 3D seismic reflection data facilitates identifying the seismogenic faults in Cases 1, 4, 7 and 8 (Eyre et al., 2019; Chopra et al., 2017; Hui et al., 2021b). For the rest cases with no seismic data, the focal mechanisms of mainshock events (Table 1) are utilized first to determine the properties of seismogenic faults, including nucleation depth, fault strike, and dip (Schultz et al., 2017; Zhang et al., 2019; Wang et al., 2018). Next, the fault height is derived from the spatial distribution of induced events in these cases. In addition, the fault length is estimated based on the empirical relations between the maximum moment magnitude and fault properties (Zoback and Gorelick, 2012). Besides, the b-value (slope of the Magnitude-Frequency distribution) for earthquake clusters can also function as an indication of pre-existing fault activation (Eaton et al., 2014).

A typical fault zone consists of a low-permeability fault core and two surrounding highly fractured damage zones (Fan et al., 2019; Yehya et al., 2018). The role of a fault as an impermeable barrier, a flow-conduit, or a combination of both depends on stratigraphic

juxtaposition, fault zone architecture, and permeability attributes for two components (Yehya et al., 2018). Under the strike-slip mechanism ($S_{Hmax} \geq S_v \geq S_{Hmin}$), the conduit faults (high-permeability-damage zone-dominated) usually exhibit the top or basal nucleation of induced events, whereas barrier faults instead exhibit the nucleation within or proximity to the stimulated layer (Fan et al., 2019). In addition, an actual fault in a field is a discontinuous interface dominated by frictional constitutive relations. In this study, a continuous fault zone is adopted as an approximation. Moreover, the mechanical shearing during fault slip in response to fluid injection may alter hydraulic properties (e.g., porosity and permeability) surrounding the fault zone. Thus, deformation-dependent porosity and permeability are employed in the coupled modeling to characterize such deformation effects, using the following expressions (Yehya et al., 2018):

$$\phi = 1 - (1 - \phi_0)e^\epsilon, \quad (6-1)$$

$$k = k_0 (\phi / \phi_0)^n, \quad (6-2)$$

where ϕ and ϕ_0 are deformation-dependent porosity and initial porosity; ϵ is the volumetric strain; k and k_0 are deformation-dependent permeability and initial permeability, and n is the exponent coefficient.

Integrated geological index. The vertical distance between injection depth and Precambrian Basement (D_{pb}) and the formation pressure gradient (F_{pg}) have been demonstrated as the top two geological factors that influence the induced seismicity in Fox Creek (Pawley et al., 2018; Eaton and Schultz, 2018). Specifically, the induced seismicity is susceptible to the large formation pressure and a short distance to the Precambrian basement. Therefore, the integrated geological Index (IGI) is introduced based on D_{pb} and

F_{pg} to characterize the geological susceptibility of HF-induced seismicity by using the following equation:

$$IGI = F_{pg}/D_{pb} \quad (6-3)$$

where D_{pb} is the distance from the injection depth to the Precambrian Basement, m; F_{pg} is the formation pressure gradient, Pa/m. The IGI has units of Pa/m².

For D_{pb} estimation, the stratigraphic correlations of 367 straight and deviated wells are conducted to determine the vertical distance from the Duvernay Formation to Precambrian Basement at the well sites (Figure 6.2a). The 3D reflection seismic data and prior works are also utilized to supplement the stratigraphic information for those wells without logging to the basement (Eyre et al., 2019; Eaton et al., 2018). The interpolation of D_{pb} using the sequence Gaussian Simulation (SGS) method between studied wells is conducted, and results are shown in Figure 6.2b. The Sequential Gaussian simulation method is a stochastic method of interpolation based on kriging. Its calculation procedure is as follows. (1) Determine the univariate cumulative distribution function; (2) Carry out the standard normal transformation on the original data; (3) Carry out simple Kriging interpolation in a node, and calculate its corresponding Kriging square difference; (4) According to the Kriging variance, a random residual function is generated, which satisfies the mean value of zero and the variance is equal to the normal distribution of the Kriging variance; (5) Add the generated residual $R(x)$ to the Kriging estimation, $Z(x)=Z^*(x)+R(x)$; (6) Add the simulated value generated at this point to the existing data and use it as the conditional data for future simulation; (7) Use random order to visit all nodes that need to be simulated one by one, and repeat the above calculation until all points are simulated; (8) Reverse Gaussian transform the simulation results to the original data; (9) Using different

numbers of random "seeds" produces different simulation implementations. The same procedure is applied to the F_{pg} estimation (Figure 6.2c). The pressure data for particular wells was sourced from the publicly available database and previous studies (Pawley et al., 2018; Eaton and Schultz, 2018). The IGI is finally determined based on D_{pb} and F_{pg} at the well sites and interpolated to the whole studied region using the SGS method.

Figure 6.2. Stratigraphy correlation and geological susceptibility. (a) NW-SE cross-sections of stratigraphy correlations. The left column represents related stratigraphy. (b) Map view of vertical distance (m) between the Duvernay formation to the Precambrian Basement. The induced events (gray cycle) and horizontal wells (black tadpoles) are overlapped in the contour map. (c) Map view of the formation pressure gradient (kPa/m) in the studied region.

6.2.2 Combined geomechanical index

A combined geomechanical index (CGI) is introduced to comprehensively quantify the geomechanical effects, including the static Poisson's ratio, Young's modulus, and the combined total organic content and clay content ($V_{\text{TOC+clay}}$). Values of the static Poisson's ratio, Young's modulus and the combined $V_{\text{TOC+clay}}$ are obtained by calibrating their measured values from velocity logging data with those from the core analysis experiments (Figure 6.3) (Eyre et al., 2019; Hui et al., 2021a). All three parameters are normalized (Table 6.1), and an equal weight of 1/3 is adopted here to calculate a CGI value. Given that the induced seismicity primarily concentrates on formations with low Poisson's ratio, high Young's modulus, and low $V_{\text{TOC+clay}}$ values, the CGI can function as an indicator to

characterize the geomechanical susceptibility on induced seismicity. The proposed CGI can be corroborated by the statistical trending of induced events by depth, which further indicates the applicability of CGI on the geomechanical bias for formations transected by inferred faults.

Figure 6.3. Determination of mechanical, hydraulic, and TOC+clay properties. (a-b) Relations between dynamic and static elastic parameters. The latter is obtained from the mechanical experiments, while the dynamic parameters are calculated from velocity logging data. (c-e) Relations between calculated data and measured data for TOC+clay content, porosity, and permeability.

Table 6.1 The hydraulic, mechanical and CGI properties for each formation

Formation/Property		Thickness	Porosity	Permeability	Biot	PR'	YM'	TOC+SH'	CGI
unit		(m)		(m ²)			(GPa)		
Wabamun		300	0.15	1.38E-16	0.79	0.010	0.520	0.912	0.481
Winterbun		200	0.16	1.43E-16	0.79	0.167	0.880	0.676	0.574
Woodbend Gp	Ireton	160	0.07	6.46E-18	0.44	0.583	0.010	0.010	0.201
	Duvernay	40	0.065	4.11E-19	0.44	0.917	0.080	0.029	0.342
Beaverhill Lake Gp	Swan Hills	100	0.05	7.1E-19	0.44	0.083	0.880	0.853	0.605
	Waterways								
	Slave Point								
Elk Point Gp	Gilwood	100	0.05	3.36E-18	0.79	0.583	0.720	0.941	0.748
	Praire-								
	Muskeg								
Cambrian	Upper	200	0.02	5.2E-20	0.79	0.500	0.720	0.990	0.737
	Middle								
	Lower								
Precambrian Basement		300	0.02	5.20E-20	0.44	0.500	0.720	0.979	0.733

Note: PR', YM', TOC+SH' are obtained by normalizing three values: $\frac{PR_{max}-PR}{PR_{max}-PR_{min}}$,

$$\frac{YM-YM_{min}}{YM_{max}-YM_{min}}, \frac{V_{clay+TOC_{max}}-V_{clay+TOC}}{V_{clay+TOC_{max}}-V_{clay+TOC_{min}}}.$$

6.2.3 Coupled fluid flow-geomechanical modeling.

During HF operations, hydraulic fractures generally propagate parallel to the orientation of S_{Hmax} , NE45°, in the studied region (Eyre et al., 2019; Zhang et al., 2019; Shen et al., 2019). The average injected rate, cumulative injected volume, and proppant weight per well in the area are 9.5 m³/min, 32,944 m³, and 4,009 t, respectively. In this work, the Perkins-Kern-Nordgren (PKN) model is employed to estimate the geometry of hydraulic fractures in eight studied cases as the fracture length is larger than its width in this region (Yew and Weng, 1997). In the PKN model, the elliptical cross-sections and

fixed height are set. The fracture length, width and pressure at a given time are calculated by (Yew and Weng, 1997):

$$L(t) = 0.68 \left[\frac{Gq_0^3}{(1-PR)\mu h^4} \right]^{1/5} t^{4/5}, \quad (6-4)$$

$$W(t) = 2.5 \left[\frac{(1-PR)\mu q_0^2}{Gh} \right]^{1/5} t^{1/5}, \quad (6-5)$$

$$P_w(t) = 2.5 \left[\frac{G^6 \mu q_0^2}{(1-PR)^4 h^6} \right]^{1/5} t^{1/5}, \quad (6-6)$$

where $L(t)$ is the fracture half-length, m; $W(t)$ is the fracture width, m; $P_w(t)$ is the wellbore pressure at the perforation site, MPa; G is the shear modulus, MPa; q_0 is the pumped fluid rate for each stage, m³/s; PR is the Poisson's ratio; μ is the viscosity of the pumped fluid, Pa·s; h is the fracture height, m; t is the given time, s.

The leak-off effects towards the shale matrix are regarded as negligible due to the low permeability. The average wellbore pressure derived from the PKN model is shown in Table 7.1, which will be regarded as the mechanical load for each fracturing stage in the following coupled modeling. The hydraulic properties (e.g., porosity and permeability) in faults-transected formations are also determined to quantify the pressure diffusion of fluid flow through a porous system. The porosity and permeability are derived from the logging and experiment data with calculated results in line with the core analysis data (Figure 6.3d-6.3e). Table 7.1 shows the calculated hydraulic properties for related formations. For the in-situ stress estimation, the magnitude of vertical stress (S_v) is obtained from the vertical integration of density logs. The minimum principal stress (S_{Hmin}) is estimated from the available shut-in pressure during stage completions (Figure 6.4). The gradient of S_{Hmax} is estimated by using the following expression: $S_{Hmax} = 3S_{Hmin} - 2P_p$ (Zoback, 2007). Both

principal stress gradient estimations are consistent with previous works (Shen et al., 2019) (Figure 6.4b-6.4c). Finally, the coupled fluid-flow and geomechanics modeling is conducted to quantify the fluid diffusion and stress perturbation (Haddad et al., 2020; Hui et al., 2021c).

The linear poroelasticity theory is employed in this work to quantify the fluid diffusion and stress perturbation in a porous medium (Wang and Kumpel, 2003). Two integrated equations have been demonstrated capable of characterizing the poroelastic process, which is given by:

$$G\nabla^2\vec{u} + \frac{G}{1-2PR}\nabla\epsilon - \alpha\nabla P_p = \vec{f}(\vec{x}, t) \quad (6-7)$$

$$\frac{1}{M}\frac{\partial P_p}{\partial t} + \alpha\frac{\partial\epsilon}{\partial t} - \nabla \cdot \left(\frac{k}{\eta}\nabla P_p \right) = q(\vec{x}, t) \quad (6-8)$$

where G is the shear modulus, GPa; u is the displacement vector; PR is the Poisson's ratio; ϵ is the volumetric strain; α is the Biot's coefficient; P_p is the excess pore pressure, MPa; $\vec{f}(\vec{x}, t)$ is the body force per unit volume on the solid matrix; M is the Biot modulus; k is the deformation-dependent permeability, μm^2 ; η is the dynamic fluid viscosity, cp; $q(\vec{x}, t)$ is the volume injection source rate, 1/s. Based on the prior works (Wang, 2000; Wang & Kumpel, 2003), the effect of the inertial term is minimal and hence is neglected in Eq.(7-2).

Table 7.2 Formation, fluid, fault and fracture parameters used in the coupled modeling

Formation / Fluid / Fault properties	Value	Unit
Duvernay Depth	2500	m

Rock Compressibility	6.90E-06	1/kPa
Rock Density	2500	kg/m ³
Duvernay Formation Porosity	0.065	
Duvernay Formation Permeability	3.94E-19	m ²
Fluid density	2500	kg/m ³
Fluid compressibility	4.60E-10	1/kPa
Fluid dynamic viscosity	0.4	mPa.s
Damage Zone Porosity	0.1	
Damage Zone Permeability (x, y, z)	1.00E-14	m ²
Fault Core Porosity	0.01	
Fault Core Permeability (x, y, z)	1.00E-20	m ²
Hydraulic Fracture Height	40	m
Hydraulic Fracture Width	0.0009~0.0023	m
Hydraulic Fracture Half-length	18.0~272.9	m

Figure 6.4. Treatment data and regional distribution of S_{hmin} and S_{Hmax} . (a) The treatment data for one stage completion. The red line represents the treating pressure during stimulation. The minimum principal stress could be estimated from the shut-in pressure. The fracture half-length could also be calculated based on the treatment data (Yew and Wang, 2015). (b-c) Map view of the minimum principal stress (S_{hmin}) and maximum principal stress (S_{Hmax}) gradient in Fox Creek.

6.2.4 Fault slip and aftershocks analysis

Based on the coupled modeling results, the Mohr-Coulomb criterion is then adopted to determine the spatiotemporal activation of related faults and forecast aftershocks (Catalli et al., 2013), which is given by:

$$\Delta CFS = \mu \Delta p_p + (\Delta \tau + \mu \Delta \sigma_n')$$
 (6-9)

where Δ denotes the changes of each parameter; τ is the shear stress, MPa; σ_n' is the effective normal stress, MPa; p_p is the excess pore pressure, MPa; μ is the friction coefficient. The shear stress τ is defined as positive in the slipping direction and normal stress σ as positive in the extensional direction.

It is commonly believed that faults will be activated when ΔCFS exceeds its threshold value of failure. The 2D Mohr's circle is used to characterize the original and subsequent stress states of the faults during HF stimulations (Zoback, 2007). Then, the effective normal stress σ_n' and the shear stress τ used in the Mohr's circle are calculated by:

$$\sigma_n' = \frac{1}{2}(\sigma_1 + \sigma_3) - \frac{1}{2}(\sigma_1 - \sigma_3)\cos(2\beta) - p_p$$
 (6-10)

$$\tau^l = \frac{1}{2}(\sigma_1 - \sigma_3)\sin(2\beta)$$
 (6-11)

$$\tau^r = -\frac{1}{2}(\sigma_1 - \sigma_3)\sin(2\beta)$$
 (6-12)

where σ_1 and σ_3 represent the magnitudes of S_{Hmax} and S_{hmin} , MPa; τ^r and τ^l are the shear stress in the right-lateral and left-lateral motion of the faults, respectively, MPa. β is the angle between the S_{Hmax} orientation and a fault strike. It is also worth noting that equations (7-5)-(7-7) are only valid when the strike of an inferred fault parallels to the intermediate

principal stress (σ_2). Otherwise, the effect of σ_2 on the estimation of the normal and shear stress should be considered (Fan et al., 2019). The calculated effective normal stress σ_n and the shear stress τ in the eight cases are shown in Table 7.3.

Table 7.3 Fault stress state in the nucleation position of eight cases

Cases	S_{hmax}	S_{hmin}	S_v	P_p	β	σ_n	τ	Seismic-	Focal-	Fault
	σ_1	σ_3	σ_2					derived	derived	Slip
	/MPa	/MPa	/MPa	/MPa		/MPa	/MPa	Length	Length	/cm
								/km	/km	
1	120.2±7.9	84.7±2.4	100.3±3	66.85	42	33.8±2.4	17.67	0.9		1
2	102.3±6.7	72.1±2	85.3±6.7	56.89	44	29.8±2	15.11		0.7	0.8
3	100.4±6.6	70.8±2	83.8±7.9	55.84	30	22.3±2	12.86		0.3	0.5
4	135.7±8.9	95.6±2.7	113.2±9.5	75.44	48	42.3±2.7	19.95	0.6		0.75
5	121±7.9	85.2±2.4	100.9±7.1	67.24	20	22.1±2.4	11.49		0.4	0.6
6	103.3±6.8	72.7±2.1	86.1±17.2	57.40	30	23±2.1	13.22		0.5	0.7
7	88.5±5.8	62.3±1.8	73.8±7.8	49.20	48	27.6±1.8	13.01	1.2		1.2
8	101±6.6	71.2±2	84.3±11.3	56.17	44	29.4±2	14.92	0.6		0.75

ΔCFS can also be used to predict a distribution of aftershocks following large events (King and Deves, 2015). This is because, during fault slips in one large event, the rock surrounding a fault will deform elastically. Consequently, the local stress around the fault will change, with some regions experiencing a positive ΔCFS while others a negative

ΔCFS . In areas experiencing positive ΔCFS , the fault state will move towards a critically stressed state, which increases the potential of fault reactivation and induced aftershock events. Generally, the positive ΔCFS that reaches 0.05 MPa is believed to be capable of triggering aftershocks (King and Deves, 2015). The location and magnitude of aftershocks depend on the pre-existing fault orientations and initial stress states. Finally, the spatiotemporal induced events in the eight cases are investigated by examining ΔCFS during and after fracturing stimulation.

6.3 Datasets

The historical seismicity of $M_w \geq 2.5$ up to 2020/01/31 was obtained from the Composite Alberta Seismicity Catalogue, where some events associated with mountain tectonic activities are not considered in this work (Figure 6.5). In this work, eight groups of microseismicity catalogs and resolved focal mechanisms are collected based on prior works and industrial submissions (Table 7.4) (Bao and Eaton, 2016; Eyre et al., 2019; Schultz et al., 2017; Eaton et al., 2018; Wang et al., 2018; Zhang et al., 2019).

A total of 594 fractured horizontal wells and 367 straight/deviated wells are selected in the Duvernay reservoir in Fox Creek (Figure 6.5). The fracturing stimulations have been monitored by the proximal seismological stations. The latter is used to investigate the geological and geomechanical features associated with the induced seismicity. The well logging and treatment data come from the available well-completion database. Moreover, the available 3D seismic covers the wells in Case 8. The fault interpretation, curvature and ant tracking attributes are available through prior works (Eaton et al., 2018; Ronald et al., 2019; Hui et al., 2021a).

It is worth noting that the nucleation time and position of induced seismicity exhibit a high degree of variety (Pine and Batchelor, 1983). For example, the induced seismicity in Case 2 occurred within the stimulated formations during the fracturing operations (Figure 6.6), whereas the induced events in Case 1 were triggered several weeks after all stage completions (Figure 6.6). All data is integrated into a comprehensive dataset. The availability of this dataset provides insights to explore the spatiotemporal linkage between hydraulic fracturing and induced seismicity in this region.

Figure 6.5. Map view of induced seismicity, inferred faults, and fracturing wells in Fox Creek. The base map represents Integrated Geological Index (IGI) overlaid by horizontal wells (black tadpoles), normalized injection volume per well (blue cycles), inferred faults (gray lines), known large faults (white lines), and induced seismicity (magenta cycles). The magnitude-scaled beach balls show focal mechanisms of eight mainshocks (Schultz et al., 2017; Zhang et al., 2019; Wang et al., 2018).

Figure 6.6. Spatiotemporal features of HF treatments and induced seismicity in eight cases. (a-h) The red cycle in the left chart represents induced events colored by time (Bao and Eaton, 2016; Eyre et al., 2019; Schultz et al., 2017; Wang et al., 2018; Zhang et al., 2019). The vertical grey line shows the injection volume per stage of fracturing wells. The middle and right charts show the spatial view of events hypocenters,

horizontal wells, and simulated hydraulic fractures. The magenta dashed line represents the inferred faults. The beach ball denotes the focal mechanisms of the mainshock event.

Table 6.4. Focal mechanisms of mainshocks and related operational factors

Cases	Date	Lat	Lon	M _w	Strike /°	Dip /°	Rake /°	TVD /m	Injection volume /m ³	Wellbore Pressure /MPa
1	150123	54.426	-117.309	3.6	5	87	-175	4076	11913.8	6.0
2	150114	54.364	-117.356	3.4	182	88	182	3469	26785.4	6.5
3	150118	54.500	-117.380	2.6	192	--	--	3405	31521.3	5.7
4	150208	54.361	-117.224	3.2	174	--	--	4600	38078.0	6.5
5	150808	54.385	-117.377	2.8	24	--	--	4100	28247.8	6.3
6	150819	54.476	-117.257	3.0	194	--	--	3500	68632.3	7.3
7	160112	54.434	-117.526	4.1	184	83	166	3000	31230.0	5.9
8	161129	54.348	-117.245	3.2	199	85	166	3425	45056.4	5.3

Note: Cases 1-7 are sourced from Schultz et al., 2017 and Wang et al., 2018; Case 8 from Zhang et al., 2019.

6.4 Results

6.4.1 Characterization of seismogenic faults

The spatial distributions of inferred faults in the eight cases are shown in Figure 6.6. The majority of the inferred faults are approximately north-south oriented and basement-rooted (Eyre et al., 2019; Hui et al., 2021b), cutting through the basal formation upward into the stimulated Duvernay Formation. The lineament features of induced events match well with inferred faults in all the cases (Figure 6.7-6.8). Results show that the faults

derived through ant-tracking are spatially related to induced events distributions, and directions of the inferred faults are in line with the ones from focal strikes of mainshock events (Figure 6.7). Take Case 4 as an example. Two northeast-trending faults and one northwest-trending fault are identified by the linear features of the ant-tracking attributes (Figure 6.7c). The strike of the latter inferred fault agrees with the focal strike of the M_w 3.0 event. 109 induced events spatially distributed along three inferred basement-rooted faults (Figure 6.7b). Besides its spatial distribution and direction, the original stress state of a fault also plays an essential role in its potential activation during stimulations. The Mohr circles are plotted to characterize the initial stress state of eight inferred faults before stimulations (Figure 6.9). The characterization of such circles is calculated by Equations (5) through (7). It is shown that an increase of 0.2-4.8 MPa in pore pressure is required to activate these inferred faults. Additionally, based on the rules associated with fault architecture (Fan et al., 2019), the inferred faults in Cases 2, 3, 5 and 8 are determined to be the fault-core-dominated barrier-faults, whereas the faults in Cases 1, 4, 6 and 7 are damage-zone-dominated conduit-faults activation.

Figure 6.7. The inferred faults identified by the ant-tracking approach. (a) Stratigraphy in the studied region. Blue, gray, orange, magenta, and magenta denoted limestone and dolomite, shale and mudstone, sandstone, evaporites, and crystalline rock, respectively (Eyre et al., 2019). (b) Interpreted F-F' cross-section of seismic data in Case 4. Distribution of magnitude-scaled induced events (red cycles), horizontal well (magenta line), formations (sub-horizontal colored lines), and three interpreted faults (subvertical black line) are shown. Induced events concentrate at the Precambrian Basement. (c) Horizontal cross-section of ant-tracking attributes (blue lines) in the Precambrian Formation. The lineament features of attributes are interpreted as three inferred faults. The dashed magenta line shows the position of F-F' cross-section.

Figure 6.8 Determination of inferred faults and fault scaling properties. (a) Cross-section view of inferred faults in Case 1 and 7. Fault 1 is spatially associated with two large earthquakes (Eyre et al., 2019). (b) Map view of horizontal wells, induced seismicity, and inferred faults. The background colors represented curvature attributes (Chopra et al., 2017). The red lineaments denoted inferred faults. The short line overlying wellbores represented calculated hydraulic fractures. The dashed magenta line shows the position of the W-

E cross-section. (c) 3D view of inferred faults via the ant-tracking approach in Case 8 (Hui et al., 2021b). Events distribution defined the geometry of inferred faults. (d) Relationship among various scaling parameters (fault size, fault slippage, and earthquake stress drops) for earthquakes. The fault size could be estimated based on this plot in cases without 3D seismic reflection data (Zoback and Gorelick, 2012).

Figure 6.9 2D Mohr circle plots for the original stress state of eight inferred faults prior to hydraulic fracturing. An estimated increase in pore pressure of 0.2~4.8 MPa is required to activate these faults. The short black line represents the calculation error.

6.4.2 Geological susceptibility

A geological analysis is conducted on 367 straight/deviated wells and 594 horizontal wells in the Duvernay Formation in Fox Creek. An Integrated Geological Index (IGI) is first introduced to quantify the geological susceptibility of induced seismicity in the targeted area, as shown in Figure 6.5. The IGI at a well site is calculated first and further interpolated to the whole region using the Sequential Gaussian Simulation (SGS) method. It can be clearly seen that the segment with a high IGI (≥ 55) has a clustered distribution

of the induced seismicity events, while a low IGI (< 55) is observed in the east segment, corresponding to nearly no seismicity events in the area. Thus, an IGI spatial distribution can indicate areas with high geological susceptibility to HF-induced seismicity. Such an observation can be used to guide the selection of a fracturing site in Fox Creek to mitigate future seismic risks. Overall, an IGI distribution, together with the aforementioned inferred faults, provides a geological indication of hydrology communication between stimulated wells and inferred faults, facilitating the evaluation of the geological susceptibility of induced seismicity in an area.

6.4.3 Geomechanical susceptibility

Besides the geological susceptibility, a geomechanical bias for induced seismicity also needs to be investigated. In this work, a combined geomechanical index (CGI) is proposed to assess the geomechanical susceptibility of induced seismicity in formations transected by inferred faults. Profile distribution of CGI is shown in Figure 6.10. Comparing the CGI with the induced seismicity in the vertical direction, we can see that the induced events concentrate at particular formations with a high CGI value, and the majority of induced events in the eight cases were triggered in formations with a CGI higher than 0.57. Hence, a CGI, together with an IGI and inferred faults, can indicate the geological and geomechanical susceptibility for related formations and thus provide guidance towards field HF operations to reduce potential seismicity risks.

Figure 6.10. The Combined Geomechanical Index (CGI) by depth, calculated mechanical and hydraulic parameters and combined TOC+clay content. Also shown are statistics of the number of induced events with a cut-off value of 0.5 in eight cases.

6.4.4 Triggering mechanisms of induced seismicity

The COMSOL software program is employed in this work to solve the Equations (2)-(3) via the finite element method (Hui et al., 2021c). The mechanical and hydraulic properties of formations, fractures, and faults are listed in the above tables, and the constructed coupled model is shown in Figure 6.11. Each model geometry in the eight cases is set with such values that the variety in the solid strain and stress applied on boundaries does not remarkably affect the simulation results. A zero-flow rate boundary is applied. The top surface is defined to be in a state of traction-free, whereas the displacement at the lateral boundaries and the bottom surface is assigned to zero (Fan et al., 2019; Haddad and

Eichhubl, 2020). The estimated in-situ stress and pore pressure are also incorporated into the model. The deformation-dependent porosity and permeability surrounding the fault zone are set in the model (Yehya et al., 2018). Mechanical loads corresponding to the injection volume and rate of each well are calculated and integrated into the model initialization. The regional mesh surrounding the fractures and faults is refined to better characterize the changes of Coulomb Failure Stress (Figure 6.11). In the mesh size setting of COMSOL Multiphysics, the normal size, instead of fine size or even smaller size, is set in this work to achieve a fast simulation. Under this setting, the mesh surrounding the fractures and faults is refined and other regions are set with a relatively large triangle mesh in Figure 6.11. In addition, the finite-element simulation is conducted by coupling Darcy's law and solid mechanics in the COMSOL Multiphysics to quantify the perturbation of pore pressure and poroelastic stress. The formation, hydraulic fractures and fault properties are incorporated into the Solid Mechanics module and Darcy's law module accordingly. The time dependence, tolerance method and time step are also set in the coupled modeling, which comes out with a fine convergence throughout the simulation.

Coupled hydrology-geomechanics simulations are conducted to identify the triggering mechanisms accounting for spatiotemporal patterns of HF-induced seismicity in Fox Creek (Figures 6.12). Figures 6.11c-11j showed the spatial ΔP along the fault plane when the mainshocks occurred. It is shown that the mainshocks in Case 2, 3, 5, and 8 were triggered by pore pressure changes within stimulated Duvernay formation (Figure 6.11a), whereas the mainshocks in Case 1, 4, 6, and 7 were induced by the pressure diffusion along conduit faults downwards or upwards to the nucleated positions (Figure 6.11b). Figure 6.13 shows a conceptional diagram of five identified triggering mechanisms in the studied area,

including (1) direct connection between hydraulic fractures and barrier-faults; (2) fault slip owing to downward pressure diffusion; (3) fault slip due to poroelastic stress perturbation; (4) aftershocks of mainshocks; (5) natural fractures activation surrounding faults (see Discussion for more details). The identification of these five triggering mechanisms can facilitate mitigating future seismic risks induced by fracturing stimulations.

Figure 6.11. Coupled model initialization and pore pressure changes. (a) Initialization of the poroelastic model for Case 4. The formations, well, faults and fractures are all incorporated into the model. (b) 3D mesh using the triangular elements. The mesh within and surrounding the fractures and faults is refined to obtain better simulation results. (c-j) The spatial ΔP along the fault plane when the mainshock event occurred. The mainshocks in Case 2, 3, 5, and 8 were triggered by pore pressure changes within stimulated Duvernay formation. The mainshocks in Case 1, 4, 6, and 7 were induced owing to the pressure diffusion along conduit faults downwards or upwards to the nucleated positions.

Figure 6.12. Triggering mechanisms of induced events in studied cases. (a-b) Spatiotemporal ΔCFS at the intersection between the inferred fault and connected hydraulic fracture during fracturing stimulations in Case 2 (nucleated in Duvernay formation) and Case 1 (nucleated in the basement). (c-d) Aftershocks followed by the mainshock event in Case 1 and Case 7. The majority of aftershocks are located in the region with a positive ΔCFS . (e) Horizontal cross-section of ant-tracking attributes in the Duvernay Formation in Case 1 and 8. The $M_w 3.0$ event occurred during HF operations of the north well, whereas the $M_w 1.25$ event was induced during fracturing stimulation of the south well. The dashed cycle marks the inferred fracture possibly responsible for the south low-magnitude clusters.

Figure 6.13. Conceptional diagram showing five triggering mechanisms in Fox Creek. The horizontal well has been performed multi-stage hydraulic fracturing operations. The seismogenic fault consists of a fault core surrounded by two damage zones. The barrier fault has a relatively wide fault core and thinner damage zones, while the conduit fault owns the opposite structure. The red arrow lines denote the fluid diffusion, and the yellow streamlines show the stress perturbation. The base map represents the lithology of related formations. To have a better display, the vertical and horizontal axis is not to scale.

6.4.5 Mitigation strategy of HF-induced seismicity

Given the geological and geomechanical susceptibility of induced seismicity in Fox Creek, fracturing operational factors need to be properly designed to reduce seismic risks, especially near the inferred faults in an area. Thus, the identification of inferred faults should be the first task to reduce future seismicity risks, which can be achieved by the aforementioned ant-tracking approach from the available 3D seismic reflection data. In scenarios with known faults, one effective approach is to enlarge the distance between a fracturing well and an existing fault, which can be applied before drilling a horizontal well near the known fault. Figure 6.12e shows the scenario where a seismicity risk is effectively prevented by enlarging such a distance between the fractured well and the inferred fault.

Another mitigation strategy is to decrease a fracturing job size (e.g., an injection volume) if the horizontal well has been drilled in proximity to a pre-existing fault before performing fracturing stimulation, as shown in Figure 6.14f (McGarr, 2014). The pore pressure changes in both scenarios are quite lower than the critical value (3.0 MPa in Figure 6.9b) required to activate the inferred fault. Therefore, enlarging an HF-fault distance and reducing a fracturing job size can aid in mitigating risks of potential seismic activities in Fox Creek. Moreover, the east region of the studied area has been selected as the optimal

fracturing region (Figure 6.5), as such region owns a low geological susceptibility to induced seismicity. For the HF operations in the west region with a high geological index, proper real-time monitoring with downhole and/or surface microseismicity is required during and after HF operations in the WCSB. The traffic light system regulated by Alberta Energy Regulator (AER) has been utilized to monitor the fracturing treatments. In addition, the CGI profile (Figure 6.10) suggested that the Ireton Formation is an optimal formation for HF operations as it has a low geomechanical susceptibility.

Figure 6.14. Mitigation strategy via enlarging HF-fault distance and reducing operational parameters. (a) The temporal changes of pore pressure, poroelastic stress, and CFS at the HF-Fault intersection under the original fracturing design. (b-d) The spatiotemporal ΔP_p for the original fracturing design in Case 8. Fluids diffused through the 11th stage of hydraulic fractures into the inferred fault, triggering the earthquake clusters. These induced events depicted the lineament features of the inferred fault as fluids diffused. (d) The temporal ΔCFS at the fault head in scenarios Figure 6.14e-14f. (e) The spatial ΔP_p with the HF-fault distance of 100m. (f)

The spatial ΔP_p for the updated fracturing design by canceling the 11th-13th stages and reducing fracturing job size of the 14th -16th stages.

6.5 Discussion

An advanced understanding of the triggering mechanisms of induced seismicity can facilitate mitigating future seismic risks by fracturing stimulations. Figure 6.12a shows the spatiotemporal changes of Coulomb failure stress (ΔCFS) at the intersection between an inferred fault and a connected hydraulic fracture in Case 2. It can be seen that ΔCFS at the injection depth increases significantly as time proceeds, indicating that the inferred fault belongs to a barrier type (Figure 6.13). Thus, the direct hydrology connections between hydraulic fractures are established in Cases 2, 3, 5 and 8, leading to an increase in ΔP_p along the barrier-faults plane (Figure 6.11c-11f). In Cases 1, 4 and 6, the fracturing fluids diffuse through hydraulic fractures downwards along the high-permeability damage zones of conduit faults to trigger large earthquakes in the high-CGI formations (Gilwood and Precambrian) (Figure 6.11g-11i). The spatiotemporal ΔCFS in Figure 6.12b indicates that the corresponding fault is a conduit type; as a result, a relatively large ΔCFS at the bottom of the fault triggered an earthquake ($M_w=3.6$) 14 days after the treatments. This time lag between stage completions and an earthquake is possibly attributed to a slow process of fluid diffusion and pressure accumulation within the damage zones of the inferred fault. Moreover, Case 7 demonstrated that the seismic events were triggered by the fault loading of an aseismic slip (Eyre et al., 2019). The hydrology connection can be restricted in the Duvernay formation, causing nearby aseismic slip (nearly no ΔP_p in Figure 6.11j), whereas the associated poroelastic stress perturbation outpaces the pore pressure migration and finally causes the fault slip in the high-CGI Winterburn Formation. In addition, the ΔCFS

generated by mainshocks can be used to explain the aftershocks in Case 4. As shown in Figures 6.12c- 12d, the majority of aftershocks are located within a positive ΔCFS region (King et al., 2015). Finally, the natural fractures surrounding the inferred fault are activated in Case 8, as shown in Figure 6.12e. The south well was drilled 600 m away from the large inferred fault, in comparison with only 50 m for the north well. The M_w 1.25 event was induced with a focal strike of $NE\ 28.2^\circ \pm 8.3^\circ$ and the clusters are primarily nucleated in proximity to the stimulated formation (Zhang et al., 2019), indicating the large fault is not reactivated. Instead, a small-scale inferred natural fracture is identified between the fault and south well (the dashed ellipse in Figure 6.12e) and was possibly activated during stimulations. Additionally, it is worth noting that the poroelastic stress changes are quite lower than pore pressure changes (ΔP_p) in seven cases (except Case 7) (Figure 6.12a). The maximum ΔP_p surrounding the inferred faults in seven cases (except Case 7) all reached the corresponding values that were required to cause the fault slip (Figure 7.9). Thus, ΔP_p is the predominant factor that affects the fracturing-induced seismicity in the area. Overall, the first three mechanisms are related to large magnitude induced events, whereas the rest two mechanisms are associated with relatively small magnitude events in the area. Furthermore, two types of faults are activated in this study. A barrier fault is dominated by a tight fault core, whereas a conduit fault is dominated by a well-developed fracture damage zone (Figure 6.13). Specifically, Cases 2, 3, 5 and 8 were triggered by barrier-faults activation arising from the elevated pore pressure within the Duvernay Formation. In contrast, earthquake clusters in Cases 1, 4, and 6 were induced by conduit-fault activation, owing to the pressure diffusion along conduit faults downwards to the nucleated formation.

After identifying five triggering mechanisms of induced seismicity, the fracturing operational factors can be properly designed to reduce seismic risks. It is clearly noted that the identification of inferred faults plays an essential role in reducing future seismicity risks (Atkinson et al., 2016; Schultz et al., 2020). The aforementioned ant-tracking approach can be effective in interpreting seismogenic faults from the available 3D seismic reflection data (Figure 6.7). If an inferred fault is identified prior to HF treatments, enlarging HF-fault distances and reducing fracturing job sizes can help mitigate risks of potential seismic activities. For example, Figure 6.14b-14c shows the original fracturing design in Case 8. It can be seen from Figure 6.14a that both ΔCFS and ΔP_p at an HF-fault intersection exhibit a sharp increase after the 11th stage completion, indicating the hydrologic communication between hydraulic fractures and inferred faults is established. It is worth noting that a pore pressure change is a predominant factor (accounting for 83% of ΔCFS) that affects the fault activation in this case (Figure 7.14a) (Tan et al., 2020). Then, we investigate the corresponding ΔCFS under different HF-fault distances. It is found that the maximum ΔCFS at the HF-Fault intersection is decreasing with an increase in the HF-fault distance, indicating the mitigation effect of fracture-fault hydrological communication. Therefore, a minimum of 100 m for the HF-fault distance is recommended in this case (Figure 6.14e), with the maximum ΔP_p along the fault plane only reaching 0.85 MPa (Figure 6.14d), lower than the critical value to activate this fault. As the second mitigation strategy, a reasonable fracturing job size can also be capable of reducing possible seismicity risks with known faults. Figure 6.14f depicts a revised fracturing design that could have avoided the fault activation if the 11th -13th stages were canceled and the injection volume for the 14th-16th stages was reduced by 37% accordingly. Under this scenario, a 70m HF-fault distance leads

to a maximum ΔP_p along the fault plane of only 1.21 MPa, low enough to prevent the fault slip (Figure 6.14d). Another strategy of progressive cyclic and pulse fracturing has been proposed in the literature (Zang et al., 2019). This fatigue hydraulic fracturing intends to generate an enlarged stimulated reservoir volume (SRV) zone to reduce the maximum ΔP_p along the fault during and after the stimulation. However, a field application of the technique has been applied in Pohang, Korea and triggered a 5.4 magnitude earthquake (Lim et al., 2020). Thus, more investigation is required to fully understand the consequences of such a method. Overall, enlarging HF-fault distances and reducing a fracturing job size can aid in mitigating risks of potential seismic activities in Fox Creek if the inferred faults are identified prior to HF operations (if not, the traffic light protocols are used to manage the seismicity risks). This practice will also provide insights for industrial managers to mitigate seismic hazards in Western Canada and other regions in the world by optimizing the site selection and fracturing scale of multi-stage horizontal wells.

Generally, a resolved focal mechanism of induced events exhibits relatively small misfits, which indicates the uncertainty of event locations (Zhang et al., 2019). For example, the event epicenter location in Case 8 has errors of ± 30 m laterally and ± 70 m in depth (Eaton et al., 2018). This uncertainty with respect to the position of induced events can have a negative effect on the modeling work, such as affecting the determination of a fault size and distribution. However, the relatively reliable location of an inferred natural fault can still be derived from a comprehensive analysis of 3D seismic interpretations, lineament features of distribution of events, and resolved focal mechanisms. Moreover, the integrated geological index indicates the induced seismicity in terms of map view, while the combined geomechanical index denotes the induced seismicity in terms of the profile

view. Both indexes will guide the fracturing operations regarding the selection of fracturing site and injection depth. Rather than depicting the whole region as both indexes do, the coupled modeling is conducted based on eight cases to reveal the underlying triggering mechanisms of HF-induced seismicity. In specific cases, the safe distance could be determined via coupled flow-geomechanics modeling.

6.6 Summary

This paper proposes an integrated approach to characterize the spatiotemporal nucleation of hydraulic fracturing-induced seismicity based on comprehensive datasets of eight cases. This approach advances the quantitative understanding of how geological, geomechanical and hydrological factors affect the fracturing-induced seismicity and determine the triggering mechanisms of distinctive seismicity. Results suggest that

- (1) Ant tracking and attributes inversion of 3D seismic interpretation help identify the seismogenic faults in the vicinity of fracturing horizontal wells. The inferred faults in Cases 2, 3, 5 and 8 are determined to be the fault-core-dominated barrier-faults, whereas the faults in Cases 1, 4, 6 and 7 are damage-zone-dominated conduit-faults activation.
- (2) An integrated geological Index (IGI) is introduced based on the vertical distance between injection depth and Precambrian Basement (D_{pb}) and the formation pressure gradient (F_{pg}). A combined geomechanical index (CGI) is introduced to comprehensively quantify the geomechanical effects, including the static Poisson's ratio, Young's modulus, and the combined total organic content and clay content ($V_{TOC+clay}$). Regions with a high IGI (≥ 55) and a CGI higher than 0.57 indicate

seismicity susceptibility, which is well in line with the spatial distribution of induced seismicity.

- (3) Five identified triggering mechanisms in the studied area, including (I) direct connection between hydraulic fractures and barrier-faults; (II) fault slip owing to downward pressure diffusion; (III) fault slip due to poroelastic stress perturbation; (IV) aftershocks of mainshocks; (V) natural fractures activation surrounding faults.
- (4) The east region of the studied area has been selected as the optimal fracturing region due to its low geological susceptibility. The proper real-time monitoring with downhole and/or surface microseismicity is required during and after HF operations in the west region. Enlarging HF-fault distance and decreasing fracturing job size are also two effective approaches to reduce potential seismicity risks.

CHAPTER 7 MACHINE LEARNING-BASED ANALYSIS OF HYDRAULIC FRACTURING- INDUCED SEISMICITY AND PRODUCTION FORECAST IN UNCONVENTIONAL RESERVOIRS

In this chapter, we develop a comprehensive machine-learning approach to evaluate the susceptibility of hydraulically induced seismicity, as well as forecast the shale gas production via the integration of geological, geomechanical and operational factors in unconventional shale reservoirs. The mitigation strategy in terms of operational control is proposed accordingly to mitigate the risks of induced seismicity, and the stimulation strategy in terms of operational parameters is also presented to maximize the shale gas production in shale reservoirs.

7.1 Machine learning approach to evaluate the susceptibility and mitigate the risks of hydraulically induced seismicity⁶

Abstract

Earthquakes induced by hydraulic fracturing during unconventional resource development have been frequently observed in Western Canada. The quantitative impacts of the geological, geomechanical, and stimulation factors on the induced seismicity magnitude

⁶ Hui, G., Chen S., Chen Z., et al. (2021g). Machine learning approach to evaluate the susceptibility and mitigate the risks of hydraulically induced seismicity. *SPE Journal* (Revision submitted)

remain unclear for this complicated phenomenon. Here, an integrated machine learning approach is first developed to evaluate the susceptibility of hydraulically induced seismicity that occurred in Fox Creek, Alberta. The statistical data analysis is performed to quantify the relationship between various controlling factors and the maximum magnitude of induced seismicity. Four machine learning approaches are evaluated, where Extra Tree has led to the highest coefficient of determination R^2 of 0.87. In addition, factors that mostly contributed to the induced seismicity are found to be the distance to fault, distance to Basement, minimum principal stress, cumulative injection volume, formation pressure, and the number of fracturing stages. Case study results have shown that $M > 3$ induced seismicity can be potentially mitigated if it reduces the fluid injection volume by approximately 61.8% per well-pad. This machine learning method is of practical importance to guide the industrial managers when designing fracturing parameters of horizontal wells targeting unconventional resources.

7.1.1 Introduction

The induced seismicity related to hydraulic fracturing in the development of unconventional reservoirs has increased notably in North American, West Europe, East Asia in the last decade (Atkinson et al., 2016; Grigoli et al., 2017; Lei et al., 2019; Schultz et al., 2020). In Western Canada, the majority of induced seismicity have been attributed to wastewater disposal in the Brazeau River zone (Schultz et al. 2014), hydrocarbon production in the Strachan D-3A Field (Baranova et al., 1999), enhanced oil recovery in the Rocky Mountain House region (Wetmiller et al. 1986), and hydraulic fracturing (HF) in the Fox Creek area (Schultz et al. 2017). Despite the numerous records of regional induced seismicity, only ~0.8% of fracturing wells are associated with $M > 3$ earthquakes, among

which ~6% wells for the Duvernay Formation and ~0.07% wells for the Cardium Formation (Ghofrani and Atkinson, 2020). The variety in earthquake nucleated location and formations raises the question as to the triggering mechanisms, susceptibility, and mitigation strategy of hydraulically induced seismicity in associated regions.

The triggering mechanisms of induced seismicity mainly include either the increase in pore pressure due to fluid injection or the poroelastic stress perturbation due to injection stimulation (Ellworth, 2013). However, when investigated on a local scale, the underlying mechanisms of induced seismicity exhibit a high degree of intricacy. Increasing lines of evidence show that hydraulically induced seismicity in Western Canada is susceptible to the combining control of site-specific geological, geomechanical, and operational factors (Pawley et al., 2018; Schultz et al., 2018; Hui et al., 2021a). In Fox Creek, the factors that contribute to induced seismicity have been found to be proximity to the Precambrian Basement and Swan Hills reef margins (Pawley et al., 2018), formation overpressure (Eaton and Schultz, 2018; Shen et al., 2019), critically stressed state of faults (Zhang et al., 2019), regional minimum principal stress (Pawley et al., 2018) and injection fluid volumes (Schultz et al., 2018). Although these factors successfully explain the susceptibility of induced seismicity in some cases of Fox Creek, the quantitative impacts of these factors on the induced seismicity magnitude remain unclear. In addition, if without considering site-specific conditions, the injection volume-maximum magnitude relationship may not directly be utilized to estimate the maximum moment magnitude (M_{wmax}) in response to fluid injection (McGarr, 2014; Atkinson et al., 2016; Wang et al., 2020). Therefore, a novel approach is required to quantify the effects of these factors on induced seismicity and mitigate the potential M_{wmax} during or after fracturing stimulation.

Understanding the quantified impact of various factors on induced seismicity requires a comprehensive analysis of large volumes of data. An incomplete or biased investigation of researchers on these factors might hinder the correct understanding of the susceptibility of hydraulically induced seismicity. Machine learning has been an effective approach in detecting the hidden relations among various factors and discovering the controlling factors of a particular phenomenon, providing an automatically complete result rather than a biased or incomplete one. Pawley et al. (2018) employed the machine learning method to investigate the geological susceptibility of induced seismicity and estimate the seismogenic activation potential accordingly in the Duvernay play of Western Canada. Perol et al. (2018) applied the neural network method for earthquake detection and prediction in Oklahoma, USA, providing a more robust model and detecting earthquakes 17 times more than the previous model. The machine learning approach is also documented in other prior works for susceptibility analysis and seismicity prediction (Wozniakowska et al., 2020; Asim et al., 2020). Despite achieving the practical analysis and prediction via the machine learning method, these studies failed to incorporate comprehensive site-specific geological, geomechanical, and operational factors (only one or several factors) into the machine learning algorithms. The integrated data-mining process by machine learning could provide a more robust model for susceptibility analysis and seismicity prediction.

In this study, a comprehensive machine-learning approach is first developed to evaluate the susceptibility of hydraulically induced seismicity that occurred in Fox Creek, Alberta. An integrated dataset is obtained to derive associated geological, geomechanical, and operational parameters as input variables, while the maximum moment magnitude of

each cluster is regarded as the target variable. The statistical data analysis is performed to quantify the relationship between various factors and the target seismicity magnitude. Four common computing approaches are then performed and compared by evaluating corresponding prediction performance. The optimal algorithm is determined using selected significant parameters. The seismicity mitigation study is finally conducted to optimize operational parameters to reduce the maximum potential magnitude of induced seismicity.

7.1.2 Field Background

The Fox Creek region has witnessed a significant increase in seismicity rates in recent years, which has been mainly associated with hydraulic fracturing operations (Atkinson et al., 2016; Schultz et al., 2017) (Fig.7.1). Several earthquakes with $M_w > 3.0$ in 2013-2016 have been demonstrated to be spatiotemporally linked to fracturing stimulation of multistage horizontal wells (Schultz et al., 2015; Bao and Eaton, 2016; Wang et al., 2017; Eaton et al., 2018; Eyre et al., 2019; Hui et al., 2021b, 2021c). Some $M_w > 3.0$ events are shown in Fig.7.1 with related resolved focal mechanisms. Although these horizontal wells were performed fracturing operations within the Duvernay formation, the induced seismicity nucleated in distinct formations, from the Precambrian Basement (Bao and Eaton, 2016), to the stimulated Duvernay formation (Eaton et al., 2018), and even upwards to the top Wabamun formation (Eyre et al., 2019), over a span of thousands of meters. It is also noted that the depths of these earthquakes are highly uncertain, which will be discussed in Section 5.2.

Statistically, the stimulated Duvernay formation is about 40.9 m in thickness, dominated by shale lithology. The Total Organic Carbon (TOC) content of Duvernay shale-hosted formation covers a range of 0.1%~11.1% based on 202 core samples analysis from

50 wells (Rokosh et al., 2012). The matrix porosity and permeability are extremely low, typically with a mean value of 0.065 and 394 nD (i.e., nano Darcy), respectively (Dunn et al., 2012). Thus, the hydraulic fracturing of multistage horizontal wells is performed widely in this region to enhance the permeability and develop unconventional reservoirs, showing useful field application in terms of shale gas production (Wang and Chen, 2019).

It is shown that induced seismicity rarely occurred before December 2013, which was more likely related to the location of where operators performed HF operations (left inset figure in Figure 7.1). Nearly no wells were fractured in the susceptible areas in this period. However, as many multistage horizontal wells were performed HF stimulation at the susceptible areas after December 2013, a large amount of $M > 3$ earthquakes were nucleated and reported (Schultz et al., 2017). Some clusters concentrated at a short period with a relatively large injection volume, indicating these earthquake clusters are temporally linked to the stage completions of fracturing wells. Statistics of horizontal wells give the average horizontal length of 2960 m and the number of stages of 42 per well. The injection fluid volume and placed proppant mass per well are averaged to be 56323 m^3 and 7223 t, respectively.

Figure 7.1. Map view of recorded seismicity and fracturing horizontal wells in Fox Creek. The red magnitude-scaled circle denoted the historical seismicity of $M_w \geq 1$ up to 2020/01/31. Four $M_w \geq 3.0$ earthquakes are shown with resolved focal mechanisms (Schultz et al., 2017; Zhang et al., 2019). The position of Fox Creek is marked with the orange-filled polygon. The black tadpole lines represent the trajectory of fracturing wells. The cumulative fluid injection per well-pad is depicted with blue circles. The left inset figure shows the daily observation of monitored seismicity and fluid injection volume. The right inset map shows the location of the studied area.

7.1.3 Materials and Methods

(1) Datasets description

The dataset used in this study is obtained from various publicly available sources. Specifically, the HF database (e.g., treatment data) is sourced from the GeoScout database. The range of dates used for the HF database is from 2012/01/01 to 2018/12/30 (Figure 7.1).

The earthquake catalog comes from the Canadian Composite Seismicity Catalogue. Figure 7.1 shows Four $M_w \geq 3.0$ earthquakes are also shown with corresponding focal mechanisms and origin time (Schultz et al., 2017; Zhang et al., 2019). The completion, logging, and testing data of 594 horizontal wells and 367 vertical wells targeting Duvernay Formations are also collected from the geoLOGIC Frac Database.

It is worth noting that not all seismicity events and wells in Figure 7.1 are analyzed. The clusters of earthquakes that have a direct temporal overlap of associated fracturing operations of stimulated wells and located within 5 km of these stimulated wells were selected (Pawley et al., 2018). Typically, for the $M_w 3.2$ case (Figure 7.2b), the operational parameters before the nucleated time of $M_w 3.2$ are evaluated (magenta rectangle) and the induced events located within 5 km of the fracturing well are investigated (magenta rectangle).

Furthermore, due to the nearly simultaneous fracturing stimulation within the same well-pad and their cumulative pressure and stress effect on HF-induced seismicity, the related data are obtained based on the well-pad instead of the single well. For the $M_w 3.2$ well-pad (Figure 7.2b), the cumulative operational parameters (e.g., injection volume, proppant mass) of fracturing wells and characteristic geological and geomechanical parameters within the selected region (magenta rectangle in Figure 7.2b) would be taken into account as the input parameters. Meanwhile, the maximum magnitude of selected earthquakes ($M_w 3.2$ in this case) is regarded as the target variable in this work. The aseismic cases (mostly located in the east area in Figure 7.1) are included as the control data groups in the machine learning approach, with $M_{\max}$ of zero. A total of 148 well-pads

and associated earthquake clusters are analyzed in this work. The uncertainty analysis using a well-pad rather than a single well is discussed in the Discussion section.

(2) Controlling factors of HF-induced seismicity

Generally, three kinds of factors have been considered as crucial for hydraulically induced seismicity and included as input variables: (1) the geological factors of formations and related faults; (2) the geomechanical properties of formations and related faults; (3) the operational parameters of fractured horizontal wells (Hincks et al., 2018; Pawley et al., 2018; Schultz et al., 2018).

Geological factors. The geological structure has been demonstrated as a significant factor that contributes to HF-induced seismicity. Such structural features include the proximity to the Precambrian Basement, the Swan Hills reef margins, and the pre-existing fault. Among them, the vertical distance to the Precambrian Basement and lateral distance to the Swan Hills Reef margin have been regarded as two important geological features that contribute to induced seismicity (Schultz et al., 2016; Pawley et al., 2018). Moreover, Hincks et al. (2018) reached similar conclusions via machine learning methods that injection distance to the Basement is critical to predicting risks of induced seismicity. For parameters estimation, the distance to the Precambrian Basement is obtained from the vertical distance between the bottom of the Duvernay Formation to the top of the Precambrian Basement. It is shown that only a few vertical wells drilled the basal formation. This parameter in other wells is derived from the horizon interpretation from the 3D seismic survey (Eyre et al., 2019; Ronald et al., 2019) and from prior works (Pawley

et al., 2018). The interpolation of distance to Basement between the studied wells is conducted via the Sequence Gaussian Simulation (SGS) method.

In addition, the distance to the Swan Hills reef is calculated by the lateral distance between the stimulated wells and the Swan Hills Formation margins. This parameter is also significant because the Swan Hills Formation margins represent a proxy for the hydrologically conductive faults (Schultz et al., 2016). The lateral distance of the Swan Hills Formation is measured from the fracturing site of horizontal wells to the Swan Hills reef edge (Pawley et al., 2018). The Sequence Gaussian Simulation (SGS) method is used to interpolate such lateral distance between the studied wells based on the well-documented margins in the two above references (Figure 7.3c).

Moreover, the pre-existing faults tend to be activated in the proximity of the fracturing site (Bao and Eaton, 2016). The structural lineaments from prior works are utilized in this study as a potential indication for the presence of a faulting system and as the third geological parameter (Coritis et al., 1997; Green and Mountjoy, 2005). These fault locations are known or inferred from geophysical or stratigraphic information in the Western Canada Sedimentary Basin (black line in Figure 7.1). The distance to such a known fault is computed by the shortest distance between the fracturing well site and its nearest large fault.

Geomechanical factors. In terms of geomechanical factors, the gradient of minimum principal stress (S_{hmin}) and formation pressure (P_p) are included to characterize the variance in the in-situ stress field and formation overpressure features (Pawley et al., 2018; Eaton and Schultz, 2018). It is worth noting that the formation pressure should be involved in the geological features. However, the formation pressure, in combination with the in-situ stress

tensors, could depict the original stress state of the potential seismogenic fault (Zoback, 2007). Thus, we regard it as the geomechanical factor in this work. Moreover, the formation overpressure has been demonstrated as an important parameter in HF-induced seismicity (Eaton and Schultz, 2018). This is because the formation overpressure represents large reservoir energy, and a small additional pressure perturbation during HF operations might cause the critically stressed fault to slip and trigger induced seismicity.

Specifically, the previous model for stress and pore pressure in the Fox Creek area has been adopted in this work (Shen et al., 2019). Such a model could calculate both parameters within the Duvernay based on an extensive analysis of high-quality microfrac data in the area. In addition, the available instantaneous shut-in pressure and closure pressure, derived from the pressure decline analysis of fracturing wells (Zoback, 2007), has also been supplemented to improve the data quality of this model. Both sources of data are combined to depict the distribution of minimum principal stress and formation pressure via the Sequential Gaussian Simulation (SGS) method.

Operational factors. The operational parameters that influence hydraulically induced seismicity mainly consist of cumulative injection volume, cumulative proppant mass, horizontal length, number of fracturing stages, and orientation of fracturing well lateral (Schultz et al., 2018; Wang and Chen, 2019). The first four parameters would serve as the considerable hydraulic energy into the related formations and possibly activate the critically stressed faults. The last parameters (fracturing orientation) play an important role in the HF-induced seismicity, given that the seismogenic faults tend to be N-S oriented in the studied region. The target variable in this work is the maximum moment magnitude (M_{wmax}) of selected earthquake clusters in the vicinity of the fracturing site. Using this

target variable, we can not only discern the aseismic wells but also discover crucial factors that contribute to the M_{wmax} .

In addition, the operational parameters usually have a positive influence on the target variable. Generally, the increase in injection volume and fracturing stages represents more hydraulic fractures to be generated within the stimulated Duvernay Formation. Meanwhile, the enlarging placed proppants and horizontal lengths are usually accompanied by a larger stimulated reservoir volume (SRV). Both scenarios would increase the likelihood of a hydraulic connection between the stimulated well and pre-existing seismic faults that might also cause the fault slip and trigger the induced seismicity.

(3) Machine learning algorithms

Here, we incorporate the comprehensive site-specific geological, geomechanical, and operational factors into the machine learning algorithms. The integrated data-mining process via machine learning could provide a more robust prediction model for HF-induced seismicity. The machine learning approach consists of two important steps, including the preprocessing of input parameters and optimizing of computing algorithms. First, the input parameters usually show a broad range of values, which may reduce the efficiency of machine learning modeling (Table 1). Thus, the data normalization is conducted to rescale the parameters to the normal distribution with a range of 0 ~ 1, which could improve the training efficiency of computing algorithms. The data preprocessed and standardization have been well documented in previous works (Wang and Chen, 2019).

Some particular computing methods are selected and compared in this work. The neural network is the most widely used machine learning algorithm, which has been successfully applied in various fields of engineering. In this study, its performance can be

taken as the benchmark (LeCun et al., 2015). The ensemble methods include Gradient Boosting Decision Tree (GBDT), Artificial Neural Network (ANN), and Extra Tree (ET). Such methods generate a large number of base learners in a parallel or serial manner and then use voting or averaging strategy to combine these learners so that the generalization performance and stability of the model are significantly improved (Breiman et al., 2001; Freund and Mason, 1999; Geurts et al., 2006). When constructing a decision tree, the extreme trees use all training samples and adopt a randomization strategy for the division. These differences between ET and RF prompt reducing the bias and variance of the model. Therefore, such four machine learning approaches are compared and evaluated in this work. Based on the input and output variables, these four algorithms are performed and compared by evaluating corresponding prediction performance. Specifically, this process is usually achieved by three steps. First, the input parameters are randomly divided into two groups: the training group (80%) and the test group (20%). Then, different data-driven approaches are performed to run the machine learning models using the training and test groups. Finally, the performance of these models is evaluated by using the mean squared error (MSE) and the coefficient of determination (R^2), which is given by:

$$MSE = \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n} \quad (7-1)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (7-2)$$

where y_i is the normalized value of the i^{th} parameter; $\hat{y}_i$ is the predicted value of the i^{th} parameter; $\bar{y}_i$ is the mean value of parameters; n is the number of parameters.

Figure 7.2. Schematic diagram of four selected computing algorithms. (a) Neural Network. (b) Gradient boosting decision trees. (c) Random Forest. (d) Extra trees.

Four selected algorithms are performed and compared by evaluating corresponding prediction performance. Specifically, a total of 1000 model runs are performed for each computing approach. The prediction model is built up based on the average prediction performance of such 1000 model runs. For each run, the prediction model is trained using 80% of the collected data while tested using the remaining 20% data randomly. Moreover, the parameters are selected by order of feature frequency. In addition, the optimized approach is determined by evaluating the corresponding prediction performance (R^2). It is worth noting that not all input variables are closely linked to the target variable. The feature selection process is conducted to eliminate some relatively insignificant parameters. The

significant parameters are then selected by assessing the significance of the studied parameters on prediction models. Finally, the optimized prediction model is determined, which should have few features (low uncertainty) but with a high performance (R^2) and a low mean squared error (MSE).

The conceptual model for the workflow of the prediction model of HF-induced seismicity via the machine learning approach is shown in Figure 7.3. The conceptual model of Duvernay shale reservoirs development via multistage horizontal wells is shown in Figure 7.3a. Fig. 3b illustrates the controlling factors of HF-induced seismicity in terms of geological, geomechanical, and operational parameters. The bottom figure shows the time window and distance requirement used for data screening. For example, the operational parameters before the nucleated time of M3.2 are evaluated, and induced events within 5km of the fracturing well are investigated (blue rectangle). Figure 7.3c shows the optimization of the prediction model via different computing algorithms using controlling factors as input variables.

Figure 7.3. Conceptual model for the workflow of seismicity prediction via machine learning approach. (a) Conceptual model of HF-induced seismicity and seismogenic fault. (b) The controlling factors of induced seismicity in terms of geological, geomechanical, and operational parameters. The bottom figure shows the time window and distance requirement used for data screening. The operational parameters before the nucleated time of M3.2 are evaluated and induced events within 5km of the fracturing well are investigated (blue rectangle). (c) Conceptual prediction model of seismicity activity via different computing algorithms.

7.1.4 Results

(1) Determination of geological factors

Distance to Precambrian Basement. Figure 7.4a illustrates the NW-SE cross-sections of stratigraphy correlations, including the logging responses, lithology type, and formation thickness for associated formations. Based on the logging features, seismic interpretation results and prior works (Pawley et al., 2018), the map view of distance to Basement is shown in Figure 7.4b. It is noted that the distance to Basement has a decreasing trend from the western seismicity-susceptible area to the eastern aseismic area. Therefore, the distance to the Basement has a negative effect on the induced seismicity.

Distance to Swan Hills Reef Margins. Figure 7.4c shows the map view of lateral distance to the Swan Hills reef margins. The boundary of the reef edge is remarkable in this studied region, which also matches well with previous studies (Schultz et al., 2017; Pawley et al., 2018). It is shown that induced seismicity concentrates at regions in proximity to the reef edge, which further corroborates that the Swan Hills Formation margins represent a proxy for the hydrologically conductive faults (Schultz et al., 2016).

Distance to large faults. Figure 7.1 also shows the map view of such structural lineaments, which serves to highlight regions that are characterized by faulting deformation zones. It is shown that locations that are proximal to structural lineaments are less vulnerable to HF-induced seismicity. Such a phenomenon suggests that the distance to the large known fault may not be the significant parameter that influences the induced seismicity.

Figure 7.4. Determination of input parameters. (a) Section views of stratigraphy correlations showing logging responses, lithology type, and formation thickness for associated formations. The left column represented the associated stratigraphy in Fox Creek. Different background colors denoted the primary lithology for each formation. The gray, blue, orange and pink colors represent shale, limestone, sandstone, and evaporite,

respectively. The right correlation shows the characteristic features of Gamma Ray (GR), Acoustic (DT), and Deep Resistivity (RT) logging for different formations. The inner map denotes the position of five selected wells in Fox Creek. (b) Vertical distance to Basement. (c) Lateral distance to Reef Edge.

(2) Determination of geomechanical factors

Formation pressure. Figure 7.5a shows the map view of formation pressure in Fox Creek, which is in line with previous works (Pawley et al., 2018; Shen et al., 2019). It is noted that the southwest of the studied region owns a high degree of formation pressure, which roughly corresponds with the considerable induced events. Therefore, the formation overpressure within the Duvernay Formation poses a significant effect on HF-induced seismicity.

Minimum Principal Stress. Figure 7.5b illustrates the map view of the minimum principal stress, which is derived from the well-documented database (Shen et al., 2019). It is noted that the magnitude of S_{hmin} in the studied region has a decrease trending from the southwest to the northeast. Thus, the seismicity-susceptible area favors a large magnitude of S_{hmin} in this region.

(3) Determination of operational factors

Figure 7.1 shows the injection volume of fracturing fluid per well-pad. It is shown that seismicity tends to be triggered in regions with a high amount of injection volume. Figures 7.5c-7.5d show the map view of other operational factors of fracturing horizontal wells in Fox Creek. It is noted that the induced seismicity also occurred in regions with a relatively high proppant mass and the number of fracturing stages.

Figure 7.5 Map view of input geomechanical and operational factors and induced events. (a) Formation pressure; (b) Minimum principal stress; (c) number of fracturing stages; (d) total proppant mass.

(4) Prediction model via machine learning approach

Input and output parameters evaluation. Based on the map view of controlling factors, it is shown that the occurrence of induced events favors a short distance to the Basement (Figure 7.4b) and the reef margins (Figure 7.4c), high formation pressure (Figure 7.5a) and high minimum principal stress (Figure 7.5b), large injection volume (Figure 7.1) and proppant mass (Figure 5d). The comparison of distribution between induced seismicity and studied parameters suggests that the distance to Basement, formation overpressure, minimum principal stress, injection volume and proppant mass own close correlations with

induced events. The input and output variables and statistical properties of such variables are shown in Table 7.1.

Table 7.1. Statistical properties of input parameters and output variables used in this study.

Type	Parameters	Units	Min	Max	Mean	Standard deviation	Source
Geological	Distance to Fault	(m)	75	19471	7198	4503	Well completion, Schultz et al.2016, Pawley et al.2018
	Distance to Basement	(m)	160	548.21	349.3	104	
	Distance to Reef	(km)	5.7	10.9	6.4	1.1	
Geomechanical	Formation pressure	(MPa)	44.4	67.0	58.8	5.6	Treatment data and Shen et al.2019
	S _{hmin}	(MPa)	50.1	90.0	75.3	10.4	
Operational	Fluid Pumped	(m ³)	4194	470118	56811	65497	Well completion and Treatment data
	Proppant Placed	(t)	249	53366	7148	9382	
	Hori-length	(m)	368	16724	2931	2910	
	Frac-stages		2	330	41	53	
	Well orientation	(°)	0	135	106	54	
Output	M _{wmax}		0	4.1	0.71	1.21	Seismicity catalog

Figure 7.6 shows the Pearson correlation matrix of studied parameters, illustrating the quantitative relationship between any two parameters. It is shown that the target variable (M_{wmax}) increases with the enlargement of formation overpressure, the minimum principal stress, distance to fault, injection volume, proppant mass, horizontal length, and fracturing stages. Additionally, the target M_{wmax} has a negative correlation with the distance to the Basement. It is worth noting that the distance to the reef edge and wellbore orientation contribute less to the target variable in comparison with other parameters. It is

also shown that all four operational parameters have a positive influence on the target variable. This could be attributed to the fact that the fracturing job size poses a direct effect on the magnitude of the induced seismicity.

Moreover, among all geological and geomechanical parameters, the distance to the Basement has the largest absolute value of the Pearson coefficient, indicating that this parameter poses a more significant influence on the M_{wmax} than other parameters. This paramount influence can be explained by the possible hydraulic connection between basement faults and stimulated well. Once proximity to the Basement, the fracturing fluids tend to migrate vertically through permeable fracture or fault networks to the basement faults, increasing the pore pressure within the basement faults to cause the fault slip (Galloway et al., 2018; Hincks et al., 2018; Pena et al., 2020).

Algorithms comparison and features selection. Although the Pearson correlations provide insights into the linear relationship between two parameters, they fail to depict other relationships, such as the curvilinear correlations, which might pose a negative effect on the robustness of the prediction model (Wang and Chen, 2019). Thus, the feature selection process needs to be conducted using the data-mining model via the Python software program. Such a model integrates all the input variables and the target variable to find their relationships. Figure 7.6b shows the normalized frequency of ten studied parameters, indicating the importance of parameters in the computing prediction models. The importance of studied parameters is characterized in the order of decreasing importance by the distance to fault, distance to Basement, minimum principal stress, cumulative injection volume, formation overpressure, number of fracturing stages, cumulative proppant placed, wellbore orientation and distance to Reef.

This result is consistent with the Pearson correlations, except for the total proppant placed, ranking the third least significant parameter in prediction models. This could be explained by the fact that the cumulative injection volume owns a close linear correlation with total proppant mass. Figure 7.6a shows that the Pearson coefficient between cumulative injection volume and cumulative proppant placed reaches 0.95, indicating that the cumulative fluid injection volume is well proportional with cumulative proppant placed. Such relations account for the relatively low frequency of cumulative proppant in the Pearson correlations.

Figure 7.6. Relationships between two parameters and feature importance. (a) Pearson correlation matrix of studied parameters, illustrating possible interconnectivity between any two parameters. (b) The normalized frequency of studied parameters. The distance to the Basement, cumulative proppant placed, minimum principal stress gradient, and cumulative injection volume is four critical parameters in the computing models.

Figure 7.7 shows the statistical prediction performance of the tested dataset using four algorithms as a function of the number of selected parameters. The prediction results have two meanings. First, the tested dataset with six selected parameters has a large coefficient of determination (R^2) in all algorithms, which achieves the goal of high prediction performance with fewer selected parameters. Second, the average R^2 of the tested dataset using six selected parameters gives the value of 0.791 for ANN, 0.799 for RF, 0.870 for ET and 0.811 for GBDT. Furthermore, the average mean-squared errors (MSE) are computed to be 0.249 for ANN, 0.189 for RF, 0.130 for ET and 0.187 for GBDT.

Therefore, the Extra Tree (ET) approach has the best prediction performance in comparison with other methods, as it has the largest R^2 and lowest MSE using six selected parameters. Figure 7.7b shows the statistical prediction performance of the tested dataset

using the ET approach. Consequently, the Extra Tree approach is selected to develop the prediction model of M_{wmax} in this work.

Figure 7.7. (a-d) The statistical prediction performance of the tested dataset using four algorithms as a function of the number of selected parameters. These parameters are selected by order of feature frequency.

Prediction model and seismicity mitigation study. A significant application of the M_{wmax} prediction model in this work is to optimize the operational parameters under site-specific geological and geomechanical conditions in Fox Creek. Four cases of $M_w > 3$ earthquakes

are selected to demonstrate the practical field application of prediction models using the ET approach. Their positions are already shown in Figure 7.1. Four induced events with magnitudes of 3.05, 3.12, 3.6, and 4.1 were triggered because associated operational parameters were not optimized in advance to reduce seismicity risks.

The application of the prediction model follows specific steps. First, we need to investigate the relationships between fluid injection and placed proppant. Here, for practicality, the fluid injection of a single horizontal well is analyzed rather than that of a well-pad. Figure 7.8a depicts the linear relationship between cumulative fracturing fluids and cumulative proppant placed per well based on fracturing datasets. It is shown that the upper and lower bound for both parameters could be determined. This strong linear relationship could facilitate determining the optimum operational parameters by the prediction model.

Next, the optimal cumulative injection volume and proppant mass are derived from the prediction model, as shown in Figure 7.8b-7.8d. The pink circles denote the original operational parameters that triggered the corresponding event in three cases. It is also noted that the occurrence of three large magnitude earthquakes is all attributed to a large amount of fluid injection volume ($>150000 \text{ m}^3$) and proppant mass ($>15000 \text{ t}$) for the whole well-pad. Given that the magnitude of 2.5 has been demonstrated to be the long-term detection threshold for induced seismicity in Western Canada (Schultz et al., 2017), this threshold is adopted in this work to optimize the proppant mass and injection volume in three cases.

Finally, the red rectangular region is determined to illustrate the optimal range for operational parameters that might trigger a maximum $M_w 2.5$ earthquake. Table 2 shows the comparison of original and optimal injection volume and proppant mass in three cases.

It is worth noting that the optimal proppant mass and fluid volume in 3.05, 3.12, 3.6 cases would have been designed to be less than approximately 70000 m³ and 10000t, 70000 m³ and 10000t, 80000 m³ and 10000t, respectively. In other words, if the cumulative injection volume per well in three cases is reduced by 58.8%, 71.1%, and 55.6%, respectively (61.8% on average), the risks of $M > 3$ induced seismicity could be mitigated based on the prediction model.

However, the M_w 4.1 case exhibits a different pattern in comparison with the first three cases (Figure 7.8e). The cumulative injection volume and proppant mass are only 31237 m³ and 3718 t, even comparable with optimal parameters in three cases. Obviously, the cumulative injection volume-maximum magnitude relationship does not work in this case (McGarr, 2014). This abnormality could be explained by the fact that the hydraulic fractures propagated and directly connected with pre-existing faults (Figure 7.8f) (Chopra et al. 2017), causing the fault slip and triggering the red-light event. Thus, the conventional injection volume- M_{wmax} relationship is not suitable for explaining the cases that exist a direct hydraulic connection between stimulated wells and seismogenic faults, consistent with prior works (Atkinson et al., 2016; Wang et al., 2020). Therefore, the mitigation strategy in M_w 4.1 case should enlarge the distance between the fracturing site and known faults to mitigate the well-fault hydraulic connections. If so, based on the prediction model, the possible M_{wmax} could have been less than 1.0 (Figure 7.8e).

Overall, this prediction model could be utilized to optimize cumulative fluid volume and proppant mass to reduce seismic risks under site-specific geological and geomechanical conditions. It is of practical importance to guide the industrial managers when designing fracturing parameters of horizontal wells targeting unconventional

reservoirs. Although this work concentrated on the Duvernay Formation in the Fox Creek region, this machine learning process could be accessible for investigating seismicity susceptibility and proposing mitigation strategies accordingly in other formations of other regions.

Figure 7.8. (a) The relationship between cumulative fracturing fluids and cumulative proppant placed based on the fracturing datasets. (b-e) The optimal cumulative injection volume and proppant mass by the prediction model. The color scale bar represents the expected magnitude of induced seismicity. The pink circle denotes the original operational parameters that triggered the corresponding event. The black rectangular shows the optimal operational parameters range that could mitigate risks of large magnitude earthquakes. Two white lines represent the upper and lower bound for both parameters (Figure 7.7a). (f) Map view of a horizontal well, induced seismicity, and inferred faults in the M_w 4.1 case. The base map represented curvature attributes derived from 3D seismic data (Chopra et al., 2017). The dashed red lineaments denoted two inferred faults. The short line overlying the horizontal wellbore represents hydraulic fractures.

Table 7.2. Comparison of original and optimal injection volume and proppant mass for HF-pads in three cases

Original			Optimal			Comparison	
M_{wmax}	Cumulative Fluid Pumped (m ³)	Cumulative Proppant Placed (t)	M_{wmax}	Cumulative Fluid Pumped (m ³)	Cumulative Proppant Placed (t)	Reduction percent of injection (%)	Reduction percent of proppant (%)
3.05	169788	16170	2.5	70000	10000	58.8	38.2
3.12	242006	22409	2.5	70000	10000	71.1	55.4
3.6	180206	19806	2.5	80000	10000	55.6	49.5
Average	197333	19462	2.5	73333	10000	61.8	47.7

7.1.5 Discussion

(1) Screening criteria of studied datasets

For the errors of well-pad data in the responding M_{wmax} variable, we also perform the machine learning method using the dataset of a single horizontal well in comparison with that of the whole HF pad. It is shown that the coefficient of determination in the model with the single well is only 0.53, less than 0.87 in the model with the well-pad. The low prediction performance using the single well might attribute to the nearly same geological, geomechanical and operational factors for single wells within the same HF-pad, which might reduce the prediction effectiveness in the model (parameter redundancy). Therefore, the well-pad-based data have a better performance in the prediction model via the machine learning method, which further corroborates the robustness of the well-pad-based data used in this work.

(2) Data quality and uncertainty analysis

We use various public data sources to derive the input geological and mechanical parameters. The data quality of these parameters depends on the robustness of such public data. For example, the distance to known fault and Swan Hills are primarily derived from the previous work (Coritis et al., 1997; Schultz et al., 2016). Additionally, the distance to the Basement, the stress, and the pressure model based on prior works are further developed using the available logging and treatment data in this region (Pawely et al., 2018; Shen et al., 2019). Therefore, such data quality is restrained by both the public data and measured data from the logging and treatment equipment (Figure 7.8a). The same measurement error may exist in the operational factors include the cumulative injection volume, proppant mass, and other operational factors.

In addition, the uncertainty analysis of output M_{wmax} is also conducted. This parameter has been generally derived from the focal mechanisms of induced seismicity. However, owing to the monitoring uncertainty of seismology networks, the M_{wmax} shows a certain uncertainty in terms of magnitude. Moreover, the focal depth of induced seismicity is also conducted in this research. Specifically, in the ToC2ME project, aided by the advanced seismology networks, the resolved focal mechanisms of induced seismicity exhibit relatively small misfits (Zhang et al., 2019). Specifically, the event epicenter location in the ToC2ME case owns the errors of ± 30 m laterally and ± 70 m in depth (Eaton et al., 2018). However, in other cases with sparsely distributed seismology stations, the uncertainty of such focal depths is often greater than ± 1 km.

(5) Features selection

In this work, the wellbore orientation has been supplemented as input parameters and the results are shown in Figure 7.6b. It is shown that this parameter has a low rank in

the model. Such poor performance may be explained by the fact that the majority of the selected well-pad have the wellbore orientation of NW-SE (112 out of 148 wells, 83%). Therefore, the difference of this parameter in this work has relatively less influence on the prediction results.

We also conduct the machine learning methods using the input variable of the coordinates of x and y. In comparison with the first prediction model (Figure 7.6b), the new results show that the first six parameters are nearly the same as the first prediction model (Figure 7.9b). The distance to fault and formation pressure has an increasing role in cases without x and y coordinates. This might be attributed to the fact that coordinate x has been related to the distance to fault and formation pressure. Given that removing x and y coordinates also has a better prediction performance, we adopt the cases without x and y coordinates (Figure 7.6b).

The final six features selected for the prediction model represent the geological (Distance to fault and Basement), geomechanical (Minimum principal stress and formation pressure), and operational factors (cumulative fluid pumped and the number of stages). Such results further corroborate the prior works (Pawley et al., 2018; Hincks et al., 2018). Some other features that we didn't consider in this work include lithium concentration, dolomite occurrence, natural seismicity rates and others. The reasons for neglecting these features are the unavailability of a database related to these features and their relatively low importance in prior works (Pawley et al., 2018). However, if obtaining the accessibility of this database, subsequent studies on these factors can be conducted.

It is also worth noting that the distance to a large known fault has a high rank in the prediction model. This may be attributed to the fact that the selected well-pads have a

certain distance from these faults (Figure 7.1). In other words, the selected datasets themselves pose certain effects on the prediction results. Another interesting phenomenon is that the wells surrounding these faults own a high amount of 12-month natural gas production equivalent (the volume of condensate oil is transferred to that of shale gas) (Figure 7.9c). This may be attributed to the natural fractures that usually develop in the vicinity of natural faults, in which the hydrocarbons generally accumulate and are easy to be produced due to the high permeability of fractures. Therefore, the HF-induced seismicity with a high magnitude rarely occurred in the vicinity of these faults because the majority of fracturing fluids flow into hydraulic fractures and possibly release the fracturing energy that might have triggered the induced seismicity. Meanwhile, this effect may be minimal in regions with a certain distance from these faults. However, this assumption needs more data to be supported and investigated in further studies.

(6) Computing methods

In this work, the Extra Tree (ET) method shows the best performance in the prediction model of HF-induced seismicity. ET is such an ensemble machine learning algorithm that combines the predictions from many decision trees (Geurts et al., 2006). It is an ensemble of decision trees related to other ensembles of decision tree algorithms such as bootstrap aggregation and random forest. The ET approach works by creating numerous unpruned decision trees based on the selected training dataset. Predictions are determined by averaging the prediction of decision trees in a regression case or using majority voting in classification cases. Compared to other algorithms, ET is faster in execution time because it randomly chooses the split point. Therefore, ET has a relatively better performance based on the selected input and output datasets.

Furthermore, regarding the limited 148 data points, we conducted the uncertainty analysis of the Extra Tree model via bootstrapping the training set. The results are shown in Figure 7.9b. It is noted that the calculation errors in regions used by the prediction model (blue areas in Figure 7.9d) are less than 0.07, indicating the robustness of this prediction model developed by the ET method. Further research with more datasets needs to be conducted in future studies.

Figure 7.9. (a) The treatment parameter for one stage of a fracturing well. (b) The parameter importance using input parameters of coordinates of x and y. (c) The map view of the fault zone, induced events, and 12-month gas production equivalent. (d) The calculation error of the prediction model using the ET method.

7.2 Production forecast for shale gas in unconventional reservoirs via machine learning approach: Case study in Fox Creek⁷

Abstract

Hundreds of horizontal wells have been performed fracturing operations to exploit the unconventional shale gas resources in the Duvernay Formation of Fox Creek, Alberta. Despite achieving the practical analysis of shale gas production via the data-mining approach, previous studies failed to incorporate comprehensive site-specific geological and operational factors. In this study, a comprehensive machine-learning approach is developed to forecast shale gas production via the integration of geological and operational factors. Thirteen geological and operational parameters deriving from the well logging, core experiment and treatment data are included as the input variables, whereas the 12-month shale gas production is regarded as the target variable. Results show that factors that mostly contributed to the shale gas production are found to be total fluid injection, total proppant mass, well TVD, permeability, TOC content, porosity, gas saturation, number of stages, shale content, formation pressure, horizontal length, distance to fault and Duvernay thickness. Four machine learning methods are evaluated, where the Extra Trees approach has led to the highest coefficient of determination R^2 of 0.81. A case study for Well 2 has shown that the shale gas production can be doubled if increase the total pumped volume and proppant placed mass by approximately 73% and 38%.

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7.2.1 Introduction

A large amount of unconventional oil and gas are trapped in the unconventional reservoirs in the Western Canadian Sedimentary Basin (WCSB), yet the traditional techniques cannot efficiently extract such hydrocarbons to the ground. Hydraulic fracturing operations have been performed in the last two decades to exploit unconventional resources efficiently. Hydraulic fracturing (HF) is to break the rock matrix and establish a high-permeable pathway between wells and the formation to obtain an economical production (Rubinstein and Mahani, 2015). Usually, the HF techniques are coupled with more recent advances in horizontal drilling. Specifically, during hydraulic fracturing operations, the wellbore is extended vertically downwards and horizontally for approximately 1.0 ~ 3.0 km within the target formation. Then large volumes of the mixture of chemicals, sands and water, (i.e., proppant) are injected under high pressure into the low permeable reservoirs. The high-pressure stimulation creates additional permeability by forming an array of cracks (hydraulic fractures) in the rock (Anderson et al., 2010). The hydraulic fractures usually extend 100 ~ 200 meters, which increases hydrocarbon production significantly. Hydraulic fracturing was first performed in WCSB in 1953 to extract hydrocarbons from the giant Pembina oil field, which would have produced very little oil without fracturing (Economides et al., 2000). Since then, more than 200,000 wells in WCSB have been horizontally fracked for unconventional reservoir production. Specific to the Fox Creek area, 573 horizontal wells have been performed HF operations to exploit the shale gas resources in the Duvernay Formation. These fracturing wells exhibit a spatial variation in the 12-month cumulative gas production (Fig.10).

Generally, two major controlling factors have been considered significant for shale gas production, including the geological factors and operational factors. Previous works have demonstrated that the stimulated formation thickness, porosity and permeability, gas saturation, formation overpressure, natural fractures distribution pose an important geological control for gas production (Wang and Chen, 2019). Meanwhile, the operational factors in terms of fracturing stages, horizontal length, fluid injection volume, proppant placed mass and injection depth also play an essential role in the production (Zhou et al., 2014; Kong et al., 2020). Usually, the 3D geological model is built up based on the reservoir information derived from the drilled vertical and horizontal wells. Then, the reservoir simulation is conducted to predict the production performance of new horizontal wells to be drilled. However, the reliability of production prediction largely depends on the robustness of the 3D geological model, which requires numerous formation information. In addition, the underlying physical mechanisms for fluid flow in an extremely low permeability reservoir with multi-stage hydraulic fractures are usually intricate. The numerical simulation process is rather time-consuming for shale gas productions. For example, a numerical simulation model usually has more than millions of grids to achieve convergence for the fluid flow in the dual-porosity dual-permeability medium. It may take several hours to days to run one model, making the optimization process unfeasible where hundreds of simulations are required to achieve optimal performance. A machine learning-based method, on the other hand, only takes several hours or even less for the whole optimization process. Therefore, a swift machine learning-based approach is required to be developed for production analysis based on the available geological and operational data.

The machine learning approach has demonstrated useful in detecting the hidden relations among various factors and discovering the controlling factors of a particular phenomenon. This data-driven approach provides an automatically complete result rather than a biased or incomplete one. Several attempts have been made to evaluate the well completions and propose stimulation strategies via different machine learning methods. Shelley and Stephenson (2000) concluded that the ANN-enhanced completions resulted in better overall well production than standard completion optimization methods normally used in oil and gas fields. Awoleke and Lane (2011) analyzed the data set from approximately 11,000 completions using conventional statistical techniques and employed a competitive-learning-based network to predict the potential for continuous water production from a new well. Zhou et al. (2014) classified 631 fracturing wells into four groups based on geological setting and then applied the traditional regression methods to study the correlation between well performance and well completion attributes. Montgomery and O'Sullivan (2017) proposed two regression approaches, the spatial error model and regression-kriging and successfully applied them to a large contemporary well dataset from the Williston Basin in North Dakota. Wang and Chen (2019) developed a comprehensive data mining process to evaluate well production performance in Montney Formation in the Western Canadian Sedimentary Basin. Despite achieving the practical analysis and production prediction via the machine learning approach in the above studies, these studies didn't incorporate comprehensive site-specific geological and operational factors into the machine learning algorithms. The integrated data-mining process via machine learning could provide a more robust model for production prediction for shale gas in unconventional reservoirs.

In this study, a comprehensive machine-learning approach is developed to evaluate the controlling factors of shale gas production in Fox Creek, Alberta. An integrated dataset is obtained to derive associated geological and operational parameters as input variables, while the 12-month gas production is regarded as the target variable. The statistical data analysis is performed to quantify the relationship between various factors and the target gas production. Four common computing approaches are then performed and compared by evaluating corresponding prediction performance. The optimal algorithm is determined using selected significant parameters. The prediction model is finally built up to optimize operational parameters to maximize shale gas production.

7.2.2 Field background

The Fox Creek region is located in the southwest of Alberta, within the Western Canada Sedimentary Basin. The shale gas reservoirs, widely developed within the Duvernay Formation in this region, have been regarded as an important unconventional resource play (Davis et al., 2012), which is primarily attributed to the wide application of horizontal drilling and multistage HF technology (Hughes, 2013). The Duvernay is an organic-rich shale-hosted formation and, depending on thermal maturity and position within the basin, produces natural gas liquids, or natural gas or oil (Switzer et al., 1994; Ronald et al., 2019). The Duvernay Formation is also commonly believed to be the primary source rock for the Devonian Leduc reef, Nisku, and Wabamun carbonate plays (Dunn et al., 2012). The stimulated Duvernay formation is about 40.9 m in thickness, dominated by shale lithology. The Total Organic Carbon (TOC) content of the Duvernay Formation is approximately 4.5% (Rokosh et al., 2012; Ronald et al., 2019; Eyre et al., 2019). The matrix porosity and permeability are extremely low, typically with a mean value of 0.065

and 394 nD (i.e., nano Darcy), respectively (Dunn et al., 2012; Zhang et al., 2019; Hui et al., 2021a). Thus, the hydraulic fracturing of multi-stage horizontal wells is performed widely in Fox Creek to enhance the permeability and develop unconventional reservoirs, showing useful field application in terms of shale gas production (Wang and Chen, 2019).

In this work, we gathered the production data of 573 fracturing horizontal wells from the online database. The first 12-month gas production data is used in this work as the paramount parameter to assess the production potential. Statistics of such parameter shows that the cumulative gas production per well in the first 12 months ranged from 7.6 to 1586 mmcf, averaging 445 mmcf. Figure 7.10 shows the 12-month shale gas production of 573 fracturing horizontal wells in Fox Creek. It is noted that the product exhibits a wide variety in spatial distribution. The high amount of 12-month shale gas production is located in the southwest and middle section of the Fox Creek region. Such distribution is roughly consistent with the distribution of large known fault zone. In terms of operational parameters, statistics of 573 horizontal wells give the average number of fracturing stages of 29 and horizontal length of 2195 m per well. The injection fluid volume and placed proppant mass per well are averaged to be 39912 m³ and 5241 t, respectively.

Figure 7.10. Map view of shale gas production of fracturing horizontal wells in Fox Creek. The yellow circle represents the normalized 12-month gas production per well. The position of Fox Creek is marked with the blue-filled polygon. The black tadpole lines represent the trajectory of fracturing wells. The blue triangles denote the coring wells that measured porosity and permeability used for subsequent input parameters. The inset map shows the location of the studied area.

7.2.3 Methods

(1) Controlling factors of shale gas production

Generally, the shale gas reserves are closely related to the area of interest, production thickness, effective porosity, gas saturation and formation volume factor, using the following expressions.

$$G_f = \frac{43560 Ah\Phi S_g}{B_g}, \quad (7-3)$$

$$B_g = \frac{P_{sc}}{Z_{sc}(Z_{sc}+459.57)} * \frac{Z(T+459.57)}{P}, \quad (7-4)$$

where G_f is free gas volume, scf; A is the area of interest, acres; h is productive thickness, feet; Φ is effective porosity, the fraction of bulk volume; S_g is gas saturation, fraction of void volume; B_g is formation volume factor, the ratio of reservoir condition volume to surface condition volume; P is pressure, psi; T is temperature, F; Z is real gas deviation factor, dimensionless; sc is standard conditions.

For the shale gas production of a single well, prior works have demonstrated that it is closely related with the geological factors, including formation thickness, formation porosity, gas saturation, formation pressure (Wang and Chen, 2019; Zhou et al., 2014; Kong et al., 2020). Besides, the distance to fault also plays an important part in the production amount.

In terms of geological data sources, the Duvernay thickness is determined by the stratigraphic correlation of wells that have available characteristic logging responses. The porosity, permeability and gas saturation are estimated by the experiment analysis of wells that have core samples tests. The formation pressure is derived from the sonic logging data of vertical wells. Specifically, we use the Eaton method to predict the pore pressure based on the sonic log data (Eaton, 1975), using the following equation:

$$P_p = S_v - (S_v - P_n)(\Delta t_{norm}/\Delta t)^x, \quad (7-5)$$

where P_n is the hydrostatic pore pressure, MPa; Δt_{norm} is the acoustic travel time from the normal compaction trend at the given depth, μs ; Δt is the observed acoustic travel time from the sonic log, μs ; and x is the exponent index. The calculated pore pressure is corroborated by the closure pressure during the end of stage complements (Yew and Wei,

2015). The distance to fault is gained by prior works that were inferred from geophysical or stratigraphic information (Pawley et al., 2018).

For the operational factors, the available treatment data of 573 horizontal wells are utilized to determine the total injection volume, total proppant mass, number of fracturing stages, horizontal length and well TVD (beneath the surface). Table 7.3 summarizes the controlling factors of shale gas production equivalent (the volume of condensate oil is transferred to that of shale gas) and their data source.

Table 7.3. The controlling factors of shale gas production and their data source

Target	Controlling factors		Data source
Shale gas production	Geological	Duvernay thickness /m	Well logging
		Porosity	Experiment analysis & well-logging
		Gas saturation	Experiment analysis & well-logging
		Formation pressure /MPa	Well logging & Treatment data
		Distance to fault /m	Prior works (Pawley et al.,2018)
	Operational	Total injection /m ³	Treatment data of 573 horizontal wells
		Total proppant /t	
		Number of stages	
		Horizontal Length /m	
		Well TVD /m	

(2) Machine learning algorithms

Here, we incorporate comprehensive site-specific geological and operational factors into the machine learning algorithms. The integrated data-mining process via

machine learning could provide a more robust model for production prediction for shale gas in unconventional reservoirs. The machine learning approach consists of two important steps, including the preprocessing of input parameters and optimizing computing algorithms.

First, the data normalization of input parameters is conducted to rescale such parameters to the normal distribution with a range of 0 ~ 1, which could improve the training efficiency of computing algorithms. Generally, the data is preprocessed using the following standardization expressions:

$$y_i = \frac{x_i - \mu}{\sigma}, \quad (7-6)$$

$$\mu = \frac{\sum_{i=1}^n (x_i)}{n}, \quad (7-7)$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^n (x_i - \mu)^2}{n}}, \quad (7-8)$$

where y_i is the normalized value of the i^{th} parameter; x_i is the i^{th} parameter; μ is the mean value of the parameters; σ is the standard deviation of the parameters; n denotes the number of parameters. Then, the computing algorithms are required to optimize for better performance.

The four methods we examined represent the classic type of supervised machine learning algorithms: Linear Regression, Neural Network, and tree-based methods. Linear regression is the simplest and yet powerful machine learning algorithm, which is typically be adopted as the first attempt to generate a baseline of what to be expected (Figure 7.11a). The Neural Network is such a method that could model the complex nonlinear relationship between input and output variables by imitating the biological neural network behavior (Figure 7.11b). It is robust and works great with a large amount of data. However, it suffers

from overfitting when the dataset is not large enough, which is usually the case with reservoir engineering problems (Shelley and Stephenson, 2000; Awoleke and Lane, 2011; LeCun et al., 2015). Gradient Boosting Decision Trees (GBDT) and Extra Trees (ET) are ensemble-based methods that generate a set of decision trees and report the average output. GBDT trains a new tree to fit the residual between the target and the current prediction result at each step, while the Extra Trees algorithm works by creating a large number of unpruned decision trees and predictions are made by averaging the prediction of the decision trees. (Breiman et al., 2001; Freund and Mason, 1999; Geurts et al., 2006; Genuer et al., 2017). It is essential to comprehensively evaluate various learning methods based on their prediction performance when they are applied to a field case study. Therefore, such four machine learning approaches are selected and compared to achieve a robust prediction model in this work.

Figure 7.11 Schematic diagram of four types of computing algorithms used in this work. (a) Linear regression. (b) Neural Network. (c) Gradient boosting decision trees. (d) Extra trees.

Four computing algorithms are then performed and compared by evaluating their individual prediction performance. Generally, there are three steps in the performance comparison. First, the input parameters are randomly divided into two groups: the training group (80% of original data) and the test group (the remaining 20%). Different computing algorithms are then performed to run the prediction models using the training and test groups. Finally, the performance of the four computing models is evaluated by using the mean squared error (MSE) and the coefficient of determination (R^2)

$$MSE = \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}, \quad (7-12)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}, \quad (7-13)$$

where y_i is the normalized value of the i^{th} parameter; $\hat{y}_i$ is the predicted value of the i^{th} parameter; $\bar{y}$ is the mean value of parameters; n is the number of parameters. The optimized prediction model is determined, which has few features (input variable) but with a high performance (R^2) and a low mean squared error (MSE).

Figure 7.12 shows the conceptual model for the workflow of production prediction via the machine learning approach. The conceptual model of Duvernay shale reservoirs development via multistage horizontal wells is shown in Figure 7.12. Figure 7.12b illustrates the controlling factors of shale gas production in terms of geological and operational parameters. Figure 7.12c shows the optimization of the prediction model via different computing algorithms using controlling factors as input variables.

Figure 7.12. Conceptual model for the workflow of production prediction via machine learning approach. (a) Conceptual model of Duvernay shale reservoirs development via multistage horizontal wells. (b) The controlling factors of shale gas production in terms of geological and operational parameters. (c) The optimization of the prediction model via different computing algorithms using controlling factors as input variables.

7.2.4 Results and Discussion

(1) Determination of geological and operational factors

Formation thickness. Figures 7.13a-13b illustrate the NW-SE and NE-SW cross-sections (black lines in Figure 7.13c) of stratigraphy correlations, including the logging responses, lithology type, and formation thickness for associated formations. The left column represents the associated stratigraphy in Fox Creek, with varied background colors showing the primary lithology for each formation (Ronald et al., 2018; Eyre et al., 2019). The gray, blue, orange and pink colors represent shale, limestone, sandstone, and evaporite, respectively. The right correlation shows the characteristic features of Gamma Ray (GR),

Acoustic (DT), and Deep Resistivity (RT) logging for different formations. The thickness of the Duvernay Formation at the well sites is determined based on the characteristic features of well logging (Figure 7.13a-13b). The interpolation of formation thickness between studied wells is conducted via the Minimum Curvature Interpolation (MCI) approach (Amorin and Broni-Bediako, 2010), and results are shown in Figure 7.13d. It is noted that the formation thickness has a decrease trending from northwest to southeast in the studied region.

Figure 7.13. (a-b) Cross-section view of stratigraphy correlations showing logging responses, lithology type, and formation thickness for associated formations. The left column represented the associated stratigraphy

in Fox Creek. Different background colors denoted the primary lithology for each formation. The gray, blue, orange and pink colors represent shale, limestone, sandstone, and evaporite, respectively. The right correlation shows the characteristic features of Gamma Ray (GR), Acoustic (DT), and Deep Resistivity (RT) logging for different formations. (c) The elevation of the Duvernay Formation in Fox Creek. The NW-SE and NE-SW lines show the positions of profile in Figure 7.13-13b, respectively. (d) Duvernay Formation thickness and well 12-month cumulative productions.

Porosity, permeability and gas saturation. The porosity, permeability and gas saturation data from the core analysis experiments of twenty-one coring wells (blue triangles in Figure 7.10) are firstly gathered in the studied region. Statistics of the three parameters are conducted and the results are shown in Figure 7.14a-14c. It is shown that core porosity, permeability and gas saturation lie in the range of 1.0%-10.6%, 0.007-18,165 nanoDarcy and 59.1%-92.2%, respectively. The average value of the three parameters is 5.1%, 486 nD and 40.4%, respectively. Based on the measured data from different coring wells, the MCI approach is then utilized to contour such three parameters and results are illustrated in Figure 14d-14f. It is noted that the porosity, permeability and gas saturation share some similar patterns in the spatial distribution, which suggests the close relations among these parameters.

Figure 7.14 (a-c) Statistics of porosity, permeability, and gas saturation from the core analysis experiments of the coring wells (blue triangles in Figure 7.10). (d-f) Map view of porosity, permeability, and gas saturation based on the measured data via the Minimum Curvature Interpolation (MCI) approach.

Formation pressure and distance to fault. Based on the comprehensive analysis of log data and Equation (3), the formation pressure is obtained at the well sites and the MCI method is employed to estimate the contour map in the studied region. Figure 7.15a shows the map view of formation pressure in Fox Creek, which matches well with previous works (Pawley et al., 2018; Eaton et al., 2018; Shen et al., 2019a, 2019b). It is noted that the

southwest of the studied region owns a high degree of formation pressure, which roughly corresponds with the high 12-month shale gas production.

In addition, structural lineaments from prior works are utilized in this study as a potential indication for the presence of a faulting system. These fault locations are known or inferred from geophysical or stratigraphic information in the Western Canada Sedimentary Basin (Green and Mountjoy, 2005). The distance to fault was quantified in a raster grid form by using Euclidean distance analysis to calculate the distance value to the closest lineament (Pawley et al., 2018). Figure 7.15b shows the map view of such structural lineaments, which serves to highlight regions that are characterized by faulting deformation zones. It is shown that locations that are proximal to structural lineaments correspond to a high production amount in the middle and southwest of the studied region.

Figure 7.15. Map view of input geological factors and 12-month production. (a) Formation pressure; (b) Distance to faults.

Statistics of operational factors. The operational factors, including the number of fracturing stages, horizontal length, fluid injection volume, proppant placed mass and well TVD, also play an essential role in the production (Zhou et al., 2014; Wang and Chen, 2019; Kong et al., 2020). Figures 7.16a-16d show the map view of the other operational

factors of 573 fracturing horizontal wells in Fox Creek. A comparison between these operational factors and the 12-month shale gas production (Figure 7.10) can be conducted. It is found that the total injection volume and total proppant mass have a positive effect on the among of 12-month production. The effect of these operational factors is quantified in the following section.

Figure 7.16 Map view of input normalized operational factors. (a) number of fracturing stages; (b) horizontal length; (c) total proppant mass; (d) total fluid injection volume.

(2) Machine learning-based production forecast of shale gas

Input parameters evaluation. Figure 7.17 shows the valuation of geological and operational factors with respect to 12-month shale gas production. It is found that the 12-month gas production is proportional to particular input parameters, including the porosity,

permeability, TVD, total proppant placed, total injection volume and gas saturation. We also incorporated shale content and Total Organic Carbon (TOC) content as the input parameters to supplement the important related information that is closely related to geologic properties. Figure 7.18 denotes the Pearson correlation results of input parameters in this work. The quantitative relationship is investigated between two parameters. It is noted that the target variable (12-months gas production) increases with the enlargement of some reservoir properties (gas saturation, porosity, permeability and formation pressure), and operational factors (well TVD, horizontal length, number of stages, total proppant mass and total fluid injection).

It is worth noting that the distance to fault and Duvernay thickness contribute less to the target variable in comparison with other parameters. On the contrary, the porosity and gas saturation has a large absolute value of the Pearson coefficient, indicating that reservoir properties pose a significant effect on shale gas production. This paramount effect can be explained by their contribution to the shale gas production shown in Equation (1). Moreover, all operational parameters have a positive effect on shale gas production. The increase in total injection volume and number of stages means more hydraulic fractures to be generated within the stimulated Duvernay Formation. The enlarging total proppants placed and horizontal lengths could generate the stimulated zone with a larger stimulated reservoir volume (SRV). The large well TVD represents a high formation pressure which would also have a positive effect on shale gas production. Overall, the reservoir properties and operational parameters own a positive correlation with shale gas production.

Figure 7.17. Evaluation of geological and operational factors with respect to 12-month shale gas production.

Figure 7.18. Pearson correlation matrix of studied parameters, illustrating possible interconnectivity between any two parameters.

Features selection. It is noted that the Pearson correlations only characterize the linear relationship between two parameters and hence fail to quantify other relationships such as the curvilinear correlations. Therefore, for the sake of the robustness of the prediction model, we conduct the feature selection process. We plot the Pareto chart based on the input and output parameters. For the axis of x, the normalized parameters are arranged in decreasing order according to the frequency first. For the axis of y, the corresponding relative-frequency of each normalized parameter is first estimated (left), and then the cumulative frequency distribution is obtained by adding the relative-frequency cumulatively (right). Figure 7.19 shows the normalized frequency of thirteen input parameters, suggesting the role of each parameter in the computing models. The importance of such parameters is characterized in the order of decreasing importance by total fluid injection, total proppant mass, well TVD, permeability, TOC content, porosity, gas saturation, number of stages, shale content, formation pressure, horizontal length, distance to fault and Duvernay thickness. The parameter importance in Figure 7.19 is roughly consistent with the results of Pearson correlations, except for the formation pressure, ranking the fourth-least important parameter in computing models. This could be explained by the fact that the shale content has a close linear correlation with formation pressure. Figure 7.18 shows that the Pearson coefficient between the shale content and formation pressure reaches 0.70, indicating that the shale content is well proportional to formation pressure.

Figure 7.19. The normalized frequency of studied parameters. The total injection volume, total proppant mass, depth, permeability are four critical parameters in the computing models.

Algorithm methods evaluation. The algorithm methods evaluation is also investigated. In this work, as many as 1000 model runs for each algorithm are conducted. Four common computing approaches, including the Neural Network, Extra Trees, Gradient Boosting Decision Trees and Linear Regression, are compared by evaluating corresponding prediction performance. A total of 1000 model runs are performed for each algorithm method. For each run, the prediction model is trained by utilizing 80% of the collected data and tested with the remaining 20% data. The parameters are selected by order of features frequency listed in Figure 7.19, with the number of parameters selected from 7 to 13. Figure 7.20 shows the statistics of the prediction performance of four algorithms as a function of the number of input parameters selected from Figure 7.19. It is noted that four methods have different large coefficients of determination (R^2) with different numbers of features.

The results of the number of features in terms of the R^2 and MSE are (1) Neural Network, ten features, 0.73 and 0.30; (2) Extra Trees, nine features, 0.81 and 0.17; (3) Gradient Boosting Decision Trees, ten features, 0.79 and 0.21; (4) Linear Regression, eleven features, 0.65 and 0.34. The statistical prediction performance of the four methods has been listed in Table 7.4. Overall, Extra Trees ranks the best prediction algorithm, which has the largest R^2 and lowest MSE using nine selected parameters. Therefore, we use the Extra Trees algorithm in this work to build up the final prediction model of 12-month shale gas production.

Figure 7.20. (a-d) The prediction performance of the tested dataset using four computing methods as a function of the number of selected parameters. These parameters are selected by order of feature frequency shown in Figure 7.19.

Table 7.4. The prediction performance of four computing methods using nine selected parameters.

Machine learning Methods	Number of features	Training dataset		Test dataset	
		Average	Average	Average	Average
		MSE	R ²	MSE	R ²
Neural Network	10	0.021	0.813	0.301	0.729
Extra Trees	9	0.029	0.971	0.194	0.809
Gradient Boosting Decision Trees	10	0.028	0.972	0.205	0.794
Linear Regression	11	0.033	0.670	0.342	0.653

Production forecast and fracturing parameters optimization. We employed the Extra Trees algorithm to build up the final prediction model, using five geological parameters (porosity, permeability, gas saturation, TOC content, shale content) and four operational parameters (total fluid injection, total proppant mass, well TVD, number of stages). The geological parameters of a random position are selected from the distribution of such parameters to establish the prediction model (Figure 7.14e-14f). The operational parameters are selected from the average value of available treatment data with a total fluid injection of 39,912m³, total proppant mass of 5,241t, well TVD of 3,226m and the number of stages of 29. Figure 7.21 shows the production forecast result in terms of the 12-month shale gas production and obvious spatial variation in gas production can be observed, where gas production proliferates in the west and south along the Duvernay boundary and gradually decreases to the northeast. It should be noted that the condensate rate has been converted to the natural gas equivalent in this work. Although the light blue region in

Fig.7.21 indicates the area with a low production, a significant condensate is expected to be produced based on the in-situ reservoir fluid composition. Such a production forecast provides a reliable foundation for the subsequent development of shale gas in this area.

Figure 7.21. Production forecast in terms of 12-month natural gas production equivalent via the Extra Trees approach using nine selected parameters.

Figure 7.22 shows the linear relationship between total proppant mass and total fluid injection based on the treatment dataset of 573 horizontal wells. The upper and lower bound for both parameters are determined, aiming to optimize the operational parameters in terms of proppant placed and fluids pumped by the prediction model. Then, the prediction model developed by the Extra Trees determines the optimal proppant mass and fluid pumped volume via the upper and lower bound in Figure 7.22a. Figure 7.22b-22d shows the actual three well cases. The base map in the three figures denotes the prediction

model in terms of proppant and injection, which is developed by using the selected nine paramount input factors. The white rectangular region is determined to illustrate the optimal range for operational parameters that might have a large amount of 12-month shale gas production (color bar at the right). The pink circles mark the original placed proppant and injection volume that corresponds to particular shale gas production in three wells. It is found that the original HF design of Well 3 is close to the optimal one, whereas that of the other two wells is not approaching the optimal one. Table 3 shows the comparison of original and optimal proppant mass and fluid injection in three wells. It is shown that, based on the prediction model, the optimal 12-month shale gas production in Well 1, 2 and 3 would reach 700, 850 and 1300 mmcf, if the total injection volume and proppant mass are increased by 467% and 412%, 73% and 40%, 2% and 8%, respectively.

Overall, under the site-specific geological conditions, the prediction model developed by the selected algorithm could be utilized to optimize total fluid volume and proppant mass to obtain a large amount of shale gas production. It is of practical importance to guide the industrial managers when designing fracturing parameters of horizontal wells. Although this work concentrated on the Duvernay Formation in Fox Creek, this machine learning process could be accessible for optimizing fracturing parameters for high hydrocarbon production in other formations of other regions.

Figure 7.22. (a) The relationship between total fracturing fluids and total proppant placed per well based on the fracturing datasets. (b-d) The optimal average fluid injection and proppant placed per well derived from the prediction model. The pink circle denotes the 12-month shale gas production with the original operational parameters. The white rectangular region shows the optimal operational parameters range that could have a better production performance with less fluid injection and placed proppant. Two white lines represent the upper and lower bound for both parameters.

Table 7.5. Comparison of original and optimal injection volume and proppant mass in three wells.

	Original	Optimal	Comparison
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	12 Mo Cum Prod Gas(mmcf)	Total Fluid Pumped (m ³)	Total Proppant Placed (t)	12 Mo Cum Prod Gas(mmcf)	Total Fluid Pumped (m ³)	Total Proppant Placed (t)	Incretion percent of injection (%)	Incretion percent of proppant (%)
Well 1	107	14114	1366	700	60000	7500	325	449
Well 2	449	35805	6519	880	62000	9000	73	38
Well 3	1210	44081	7861	1300	50000	8500	13	8

7.3 Summary

In this study, a comprehensive machine-learning approach is developed to evaluate the susceptibility of hydraulically induced seismicity and evaluate the controlling factors of shale gas production in the unconventional reservoirs near Fox Creek. The mitigation strategy in terms of operational control is proposed accordingly to mitigate the risks of induced seismicity, and the stimulation strategy in terms of operational parameters is also presented to maximize shale gas production. The following conclusions are drawn from two cases study.

- (1) Ten geological, geomechanical, and operational parameters deriving from the integrated dataset of Fox Creek are included as input variables, whereas the maximum moment magnitude of each cluster is regarded as the target variable.
- (2) Factors that mostly contributed to the induced seismicity are found to be the distance to fault, distance to Basement, minimum principal stress, cumulative injection volume, formation overpressure, number of fracturing stages, cumulative proppant placed, wellbore orientation and distance to Reef.
- (3) Four machine learning approaches are evaluated, where Extra Tree has led to the highest coefficient of determination R^2 of 0.87. Case study results have shown that $M > 3$ induced seismicity can be potentially mitigated if the fluid injection volume is reduced by approximately 61.8% per well-pad.
- (4) Thirteen geological and operational parameters deriving from the well logging, core experiment and treatment data are included as the input variables, whereas the 12-month shale gas production is regarded as the target variable.

- (5) Factors that mostly contribute to shale gas production are found to be total fluid injection, total proppant mass, well TVD, permeability, TOC content, porosity, gas saturation, number of stages, shale content, formation pressure, horizontal length, distance to fault and Duvernay thickness.
- (6) Four machine learning methods are evaluated, where the Extra Trees approach has led to the highest coefficient of determination R^2 of 0.809. Case studies for Well 2 have shown that the shale gas production can be doubled if increase the total pumped volume and proppant placed mass by approximately 73% and 38%.

CHAPTER 8 CONCLUSIONS AND RECOMMENDATIONS

8.1 Conclusions

In this study, an integrated approach of geology, geophysics, geomechanics and hydrodynamics is developed to characterize the hydraulic fracturing-induced seismicity in unconventional shale reservoirs. Firstly, a structural model including the faults and surfaces is developed by the multi-component 3D seismic interpretation. The local structure attributes analysis, and ant-tracking technique are then applied to identify the pre-existing faults and fractures distribution, where their distributions are calibrated by focal mechanism inversion of the mainshock events. Subsequently, a 3D geomechanical model is built, which incorporates the rock mechanics and in-situ stress regime into the structure model. Additionally, the hydraulic fracturing processes are simulated and hydraulic fractures geometry and fluid pressure distribution within the hydraulic fractures are estimated by history matching the net pressure. Finally, the fluid flow in hydraulic fractures is coupled with the geomechanical model to characterize the pore pressure diffusion and poroelastic stress perturbation that causes the fault to slip.

As the field cases, the Mw 3.6 and Mw 4.1 induced seismicity near the Crooked Lake region are investigated to evaluate the applicability of the integrated approach. Moreover, the Mw 3.2 case and Mw 4.18 cases are analyzed to explore the controlling factors of hydraulic fracturing-induced seismicity in Western Canada. Based on eight field cases in Fox Creek, the susceptibility of hydraulic fracturing-induced seismicity towards fracturing stimulations are evaluated and potential mitigation strategies are proposed to reduce future seismicity risks. Finally, a comprehensive machine-learning approach is

proposed to evaluate the susceptibility and mitigate the risks of hydraulically induced seismicity, as well as forecast the shale gas production via the integration of geological, geomechanical and operational factors in Fox Creek. The major conclusions of this dissertation are summarized as follows.

- (1) The proposed integrated approach can identify the triggering mechanisms of hydraulic fracturing-induced seismicity in tight and shale reservoirs. The flow-geomechanics model was used to compute the CFS changes and determine the reactivation of faults. The calculated results were in good agreement with the induced seismicity, both spatially and temporally. In the ToC2ME case, the cluster 1, 3, 7 and the beginning part of cluster 2 were associated with the propagation of hydraulic fractures whereas clusters 4, 5, 6 and subsequent part of cluster 2 were linked to the reactivation of natural faults and fractures.
- (2) The poroelastic effects on high-permeable damage zones of a conductive-barrier fault are responsible for fault reactivation in the Precambrian Basement and top Winterburn Formation. The empirical net injection-Mw relations are not adoptable in cases with direct HF-fault hydrological connections. The pressure diffusion and stress perturbation owing to the injection volume of 11,914 m³ fluids cause the fault slip and trigger the Mw 3.6 earthquake in the basement 40 days after the onset of operations. In contrast, the stimulation of another well with approximately 8,500 m³ volume of fluid injection facilitates poroelastic effects on the fault damage zone in the top Winterburn Formation. The Mw 4.1 earthquake was reactivated at 8 days after the initiation of treatments.

- (3) Ant-tracking interpretation provides evidence to account for the spatial distribution of earthquake clusters during HF operations. The Mw 3.0 induced seismicity was triggered by fluid diffusion through hydraulic fractures along high-permeability fault damage zones downwards into the basement. The negative shear stress gradient indicates the downward shear growth during hydraulic connections. This basal fault slip was attributed primarily to the elevated pore pressure along the fault plane in response to fracturing fluid injection.
- (4) The ML 4.18 earthquake clusters were triggered by the hydraulic connection between stimulated wells and inferred fault. The controlling factors of such hydraulically induced seismicity are listed in the order of decreasing importance by HF-fault distance, fault permeability, injection rate, fault rigidity, injection layer permeability, and Biot's coefficient.
- (5) Based on the in-depth investigation of eight field cases, five identified triggering mechanisms in the studied area, including (I) direct connection between hydraulic fractures and barrier-faults; (II) fault slip owing to downward pressure diffusion; (III) fault slip due to poroelastic stress perturbation; (IV) aftershocks of mainshocks; (V) natural fractures activation surrounding faults.
- (6) The east region of Fox Creek has been selected as the optimal fracturing region due to its low geological susceptibility. The proper real-time monitoring with downhole and/or surface microseismicity is required during and after HF operations in the west region. Enlarging HF-fault distance and decreasing fracturing job size are also two effective approaches to reduce potential seismicity risks.

- (7) Ten geological, geomechanical, and operational parameters deriving from the integrated dataset of Fox Creek are included as input variables, whereas the maximum moment magnitude of each cluster is regarded as the target variable. Factors that mostly contributed to the induced seismicity are found to be the distance to fault, distance to Basement, minimum principal stress, cumulative injection volume, formation overpressure, number of fracturing stages, cumulative proppant placed, wellbore orientation and distance to Reef. Four machine learning approaches are evaluated, where Extra Tree has led to the highest coefficient of determination R^2 of 0.87. Case study results have shown that $M > 3$ induced seismicity can be potentially mitigated if it reduces the fluid injection volume by approximately 61.8% per well-pad.
- (8) Thirteen geological and operational parameters deriving from the well logging, core experiment and treatment data are included as the input variables, whereas the 12-month shale gas production is regarded as the target variable. Factors that mostly contribute to shale gas production are found to be total fluid injection, total proppant mass, well TVD, permeability, TOC content, porosity, gas saturation, number of stages, shale content, formation pressure, horizontal length, distance to fault and Duvernay thickness. Four machine learning methods are evaluated, where the Extra Trees approach has led to the highest coefficient of determination R^2 of 0.809. Case studies for Well 2 have shown that the shale gas production can be doubled if increase the total pumped volume and proppant placed mass by approximately 73% and 38%.

The main contributions of this work are summarized as follows:

(1) This is the first attempt to apply an integrated fluid flow-geomechanical approach to characterize hydraulic-fracturing induced seismicity in Western Canada via the integration of geology, geomechanics, hydrology.

(2) The comprehensive characterization of hydraulic-fracturing induced seismicity in Fox Creek can successfully identify the triggering mechanisms and controlling factors of HF-induced seismicity and help guide the operators to propose the mitigation strategy accordingly during HF stimulations.

(3) This is the first attempt to apply an integrated machine-learning approach to evaluate the susceptibility of HF-induced seismicity in Fox Creek, which can be applied to other formations in different regions. Most importantly, such a method could be utilized to optimize total fluid volume and proppant mass to reduce the HF-induced seismicity or obtain a large amount of shale gas production via the integrated datasets of geological, geomechanical parameters and treatment data.

8.2 Recommendations

In this work, natural fractures are defined with breakups of several meters or dozens of meters, whereas natural faults are defined with thousands of meters or several kilometers. More outcrops materials should be investigated to further distinguish both terminologies. In addition, the fault plane and fault zone should be further studied in future works. The normal stress and shear stress applied to the fault plane is calculated based on the stress and pressure estimation, the increase in pore pressure to cause the fault slippage is calculated according to the Mohr-Coulomb Failure criterion. However, the fault zone is referred in the poroelastic process induced by hydraulic fracturing operations. Specifically,

the fracturing fluids diffused from the hydraulic fractures into the damage zone of the fault system. Therefore, in future works, the fault plane and fault zone should be unified and applied properly. Another important aspect is the characterization of hydraulic fractures. Here we assume one NE 45-oriented hydraulic fracture is stimulated during stage completions without considering the stress shadow or the leak-off effect. However, in future works, we should investigate the irregular hydraulic fracture networks and also consider the stress shadow or the leak-off effect during hydraulic fracturing.

Moreover, the porosity and permeability used in this work are measured in the core experiments under surface conditions. Such results of surface conditions may pose a negative effect on the research results. Therefore, in future works, more experiments data under the formation conditions should be collected instead, or calibrate the results under the surface conditions to those under formation pressure and temperatures. Furthermore, the total thickness of the Duvernay Formation is utilized in this work. However, to better characterize the properties of the Duvernay Formation, the net thickness should be employed instead. Therefore, the logging evaluation of the Duvernay Formation should be conducted to rule out the Carbon component and to obtain the net thickness within the Duvernay Formation.

The integrated fluid flow-geomechanical modeling is gradually applied to evaluate the hydraulic fracturing-induced seismicity in unconventional reservoirs, which improves the understanding of triggering mechanisms and controlling factors of such seismicity. However, the comprehensive datasets are usually obtained from the 3D seismic data and microseismicity observation, field treatment and completion data, core experiments, well logging and other sources of data, suffering from a large uncertainty. A comprehensive

multi-discipline analysis still needs to be further conducted to cope with the complexity and uncertainty of the problems.

(1) The focal mechanism based on the regional seismological network exhibited relatively small misfits, leading to the uncertainty of event epicenter's location. Errors in epicenters' location posed a negative effect on the results of focal mechanism inversion. Therefore, the high-resolution data from the dense seismology stations should be used to obtain the relatively precise focal mechanisms results.

(2) It is also worth noting that not all faults are identified prior to hydraulic fracturing operations, even with the high-resolution 3D seismic data. Therefore, a comprehensive analysis should be conducted to estimate the relatively reliable location of the inferred natural fault via integration of event epicenters, ant tracking results, focal mechanism of events and other sources.

(3) The petrophysical (e.g., porosity and permeability) and geomechanical properties (e.g., Young's modulus and Poisson's ratio) are usually employed homogeneous empirical value for many poroelastic models in this work, which might not reflect the reservoir heterogeneity and hence affect the simulation results of poroelastic modeling. However, such heterogeneity in those properties could be characterized by using a large amount of data from Tight Rock Analysis and triaxial compression experiments in the study area. Therefore, access to those large datasets should be obtained for the model's robustness.

(4) Decreasing fracturing job size has shown applicability to reduce potential seismicity risks. However, such a mitigation strategy may pose a negative effect on the production performance of associated horizontal wells in unconventional reservoirs. Therefore, we should gather more production and seismicity data to conduct the production-seismicity study to strike a balance for both factors.

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APPENDIX A SIMULATION PROCEDURES OF FRACPRO SOFTWARE

In this work, we use the FracPro software to simulate hydraulic fracture propagation. The procedures of fracture simulation work using FracPro software are shown in Fig. A1.

Figure A1. Procedures of net-pressure-history-matching via FracPro software

Specifically, the treatment data are first collected as the model input data, including the treatment pressure, slurry rate, and proppant concentration. The view of such treatment data is shown in Fig. A2.

Figure A2. Treatment data in the FracPro software

Then, the wellbore structure, including the drilling condition, perforation, and trajectory, is set with the well completion data. Next, the formation properties, including the lithology and rock mechanics, are introduced into the model. The fracturing fluid and proppant type are selected, and the fracturing stages are set accordingly based on the treatment records. Besides, the Perkins-Kern-Nordgren (PKN) model is employed in this simulation to estimate the geometry of hydraulic fractures (Yew and Weng, 1997). Finally, the friction loss and mini-frac calibration treatment are also analyzed for the history-matching of the net pressure. The results are shown in Figure A3.

Figure A3. Simulation results of net-pressure-history-matching

The spatial propagation, including the hydraulic fracture width and length, can be simulated accordingly based on the results of history-matching. The results are shown in Fig.A4.

Figure 4. Procedures of net-pressure-history-matching via FracPro software.

APPENDIX B COUPLED MODELING PROCEDURES OF COMSOL SOFTWARE

In this work, we use the COMSOL multiphysics software to simulate the coupled poroelastic process in terms of stress and pressure changes. The procedures of coupled simulation work using COMSOL software are shown in Fig. B1.

Figure B1. Procedures of net-pressure-history-matching via FracPro software

Specifically, the geometry of the model is first set based on the geological model, including the geometry of associated faults, fractures, and formations. The view of such a geometry setting is shown in Fig. B2.

Figure B2. Geometry setting based on the geological model in COMSOL software

Then, the solid mechanics of the block model is set with the initial and boundary conditions. Specifically, the boundaries of the block model are fixed. The top surface is in a traction-free state, and the lateral boundaries and bottom surface have zero displacements. The view of such a setting is shown in Fig. B3.

Figure B3. Initial and boundary conditions setting in solid mechanics

Next, in Darcy's Law module, the initial and boundary conditions are assigned based on the treatment data. For example, the initial pore pressure is assigned to the calculated results. No fluids flow in or out from the boundary of the block model. The view of such a setting is shown in Fig. B4.

Figure B4. Initial and boundary conditions setting in Darcy's Law

In the Fracture Flow module, the fluid properties (e.g., fluid density and viscosity) are set in line with the treatment data, and fracture properties (e.g., fracture porosity and permeability) are assigned to calculated results based on the empirical expressions. Moreover, the injection fluid per fracturing stage is regarded as the mechanical load, as shown in Fig. B5.

Figure B5. Fluid and fracture properties setting in Fracture Flow

Then the Multiphysics module is set by combining Darcy's law with solid mechanics. After that, the mesh type is switched to physics-controlled triangular mesh with normal size. Besides, the mesh surrounding the fractures and faults is refined to obtain a better simulation result. The mesh setting is shown in Fig. B6.

Figure B6. 3D meshes in the coupled model using triangular elements methods.

Finally, the coupled simulation is run to characterize the real-time changes of pore pressure and stress, as shown in Fig. B7.

Figure B7. The real-time pressure changes during fracturing stimulations.

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Investigation on Two Mw 3.6 and Mw 4.1 Earthquakes Triggered by Poroelastic Effects of Hydraulic Fracturing Operations Near Crooked Lake, Alberta

Author: Gang Hui, Shengnan Chen, Zhangxin Chen, et al
 Publication: Journal of Geophysical Research: Solid Earth
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An integrated approach to characterize hydraulic fracturing-induced seismicity in shale reservoirs

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Author: Gang Hui, Shengnan Chen, Fei Gu, Hai Wang, Linyang Zhang, Xinran Yu

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