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Developing a fuzzy logic-based risk assessment for groundwater contamination from well integrity failure during hydraulic fracturing

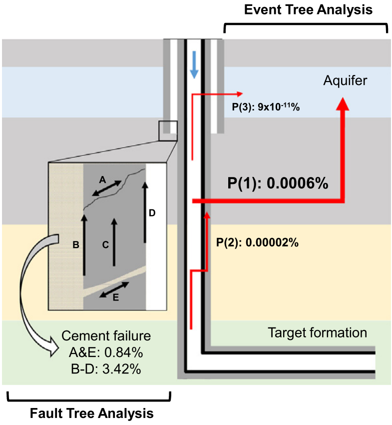
Olivia Milton-Thompson [a,*], Akbar A. Javadi [a], Zoran Kapelan [a,b], Aaron G. Cahill [c], Laurie Welch [d]

[a] Centre for Water Systems, University of Exeter, Harrison Building, North Park Road, Exeter EX4 4QF, UK
[b] Delft University of Technology, Department of Water Management, Stevinweg 1, 2628 CN Delft, Netherlands
[c] Lyell Centre, Heriot-Watt University, Edinburgh EH14 4AS, UK
[d] British Columbia Oil and Gas Commission, Kelowna, BC V1Y 8H2, Canada

HIGHLIGHTS

- Risk assessments are more successful using both numeric and linguistic data.
- Fuzzy logic represents human error more effectively than probabilistic analysis.
- Human expertise successfully bridged the data gap for cement failure in gas wells.
- Event tree analysis allows a rigorous analysis of pathways for gas contamination.
- A novel comparison of conventional versus fuzzy analysis validated fuzzy methods.

GRAPHICAL ABSTRACT



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ABSTRACT

Recent natural gas development by means of hydraulic fracturing requires a detailed risk analysis to eliminate or mitigate damage to the natural environment. Such geo-energy related subsurface activities involve complex engineering processes and uncertain data, making comprehensive, quantitative risk assessments a challenge to develop. This research seeks to develop a risk framework utilising data for quantitative numerical analysis and expert knowledge for qualitative analysis in the form of fuzzy logic, focusing on hydraulically fractured wells during the well stimulation stage applied to scenarios in the UK and Canada. New fault trees are developed for assessing cement failure in the vertical and horizontal directions, resulting in probabilities of failure of 3.42% and 0.84%, respectively. An overall probability of migration to groundwater during the well injection stage was determined as 0.0006%, compared with a Canadian case study which considered 0.13% of wells failed during any stage of the wells life cycle. It incorporates various data types to represent the complexity of hydraulic fracturing, encouraging a more complete and accurate analysis of risk failures which engineers can directly apply to old and new hydraulic fracturing sites without the necessity for extensive historic and probabilistic data. This framework can be extended to assess risk across all stages of well development, which would lead to a gap in the modelled and actual probabilities narrowing. The framework developed has relevance to other geo-energy related subsurface activities such as CO_2 sequestration, geothermal, and waste fluid injection disposal.

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* Corresponding author at: 60 Tollards Road, Exeter, EX2 6JH, UK.
E-mail address: olivia.miltonthompson@gmail.com (O. Milton-Thompson).

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1. Introduction

Unconventional hydrocarbon resource development, which involves hydraulic fracturing, is a complex engineering process with many theoretical contributors to environmental risk. These risks might include water resource contamination, water depletion, fugitive gas emissions, soil contamination, and human health impacts, many of which have been documented in the literature (Environment Agency, 2013; Vengosh et al., 2014; Ryan et al., 2015; US Environmental Protection Agency, 2016). An aspect of the process involves the injection of fluids at high pressure to fracture low permeability gas-bearing formations to allow hydrocarbons to flow. This process, known as well stimulation, has been identified as a factor that may significantly contribute to loss of well containment and lead to fugitive gas migration (Long et al., 2015; Torres et al., 2016). Jackson et al. (2013) and Osborn et al. (2011) demonstrated methane in 82% of drinking wells was of thermogenic origin suggesting it was likely from the shale and it reached shallow water due to casing or cement annulus failures (Torres et al., 2016). However, studies have disproved this connection of thermogenic methane linked directly to shale formations with papers criticizing the lack of baseline data to indicate the amount of thermogenic methane naturally present in groundwater, regardless of hydraulic fracturing (Davies, 2011; Molofsky et al., 2011; Siegel et al., 2015). Additional studies also indicated the most common mechanism for methane reaching groundwater (outside of natural migration) is the loss of casing and cement integrity (Ingraffea et al., 2014; Jackson et al., 2014). Unexpected levels of major ions and organic compounds in shallow drinking wells within close proximity to stimulation wells have been seen and indicate the migration of stimulation fluids into formations and the loss of zonal isolation during stimulation (Digiulio and Jackson, 2016; Sun et al., 2019). These casing and cement failures are most likely to occur during the well stimulation process under extreme pressures and hence compromising of these barriers during this stage has been the focus of this paper.

As well stimulation is a subsurface operation, groundwater is at particular risk for impact from compromised well integrity and has been investigated accordingly (Cahill et al., 2019; Darrah et al., 2014; Davies et al., 2014; Dusseault and Jackson, 2014; Forde et al., 2019; Humez et al., 2016; Jabbari et al., 2017; Lackey et al., 2017). General knowledge of environmental risks associated with well integrity failure scenarios, including groundwater contamination, have been used to develop industry best practises and government regulations (Considine et al., 2013; Dethlefs and Chastain, 2012; Zoback et al., 2010). For example, the likelihood of water contamination from natural gas production from the Marcellus shale was previously assessed using probability bounds analysis supported by various data sources (Rozell and Reaven, 2012). Here it was found wastewater disposal as a contamination pathway had the highest risk and uncertainty bounds, with the next highest uncertainty level in risk being fluid migration through fractures. Similarly, Ziemkiewicz et al. (2014) collected data in the field associated with the Marcellus shale and hydraulic fracturing, focusing on different risk pathways of contamination of waste fluid containment and transport. Here it was found flowback, drilling muds, and fluids all exceeded the desired limits with pits and impoundments presenting deficiencies in their containment systems, highlighting a high risk concern for potential water contamination. Meanwhile, casing and cement failure in conventional and unconventional wells in Pennsylvania were analysed using a historic database created by the state using the Cox proportional hazards model (Ingraffea et al., 2014). Here it was found between 1 and 10% of wells demonstrated structural issues within Pennsylvania and the Marcellus Shale with the main variances due to location, the inspection of records and the time at which a well was drilled. Post-2009, wells appeared to be at a significantly higher risk in cement or casing failure in unconventional compared with conventional drilling. Additionally, the current historical database used was not the best way to determine well integrity violations due to significant incomplete data sets. None of the three assessments mentioned above have focused on the contamination of groundwater and cannot indicate a clear application to other sites, particularly globally. In addition, data sets used indicated significant gaps in knowledge, presenting potentially skewed data with no clear method of handling these data gaps. Certain studies were only feasible with the historic collection of data, limiting the application of risk analysis to sites which have already experienced significant problems. This does not allow pre-emptive risk analysis on new hydraulically fractured sites. Certain models have worked on quantifying uncertainties to handle significant data gaps using sensitivity analysis during hydraulic fracturing operations (Glaser et al., 2016). Although these models demonstrate a comprehensive modelling process of individual risk pathways, only a probabilistic context has been used which presents many assumptions to the model without a direct representation of hydraulic fracturing. Comprehensive models which perform a more holistic risk analysis on the water environment are required, to include quantitative and qualitative factors such as mechanical, human, and social perspectives. There are very few risk assessment studies which take into account human experience which can be more valuable than a solely quantitative approach (Torres et al., 2016).

Risk assessments conducted in the oil and gas industry have taken a variety of approaches. Torres et al. (2016) discusses the current risk assessment techniques used in the industry along with the most appropriate methods to obtain a holistic and integrated risk analysis. Quantitative Risk Assessment (QRA) methods are most common in the oil and gas industry (Torres et al., 2016). Offshore operations, such as in the UK and Norway, widely use QRAs (Cai et al., 2013; Skogdalen and Vinnem, 2012; Torbergsen et al., 2012; Yang et al., 2018) introduced as a technique to support regulatory decisions and safety management systems (Aven and Kristensen, 2005). Traditionally, QRAs have been used to quantify risk in the design and operation stages of offshore installations, particularly for well integrity (Torbergsen et al., 2012; Vignes and Aadnoy, 2010). They generally require numerical estimates of probability and consequence of potential incidents based on engineering evaluation and mathematical techniques (NASA and BSEE, 2017). Detailed QRAs are seldom used in the oil and gas industry due to a lack of safety integrity or experience data to perform causal analysis. Consequently, simpler tools are used which do not support detailed analysis of uncertainty, common cause failures or human reliability (NASA and BSEE, 2017; Torres et al., 2016). Recently, efforts are being made to include Human and Organizational Factors in QRAs (Aven et al., 2006; Skogdalen and Vinnem, 2011), and Bayesian network techniques in the offshore industry (Cai et al., 2013; Khakzad et al., 2013) are used to support uncertainty in QRAs (Aven and Kristensen, 2005). These methods could be applied to the onshore industry (Torres et al., 2016).

Departments such as the Environmental Protection Agency, US Department of Energy and the Ministry of Defence conducted Environmental Risk Assessments (ERAs) using a variety of techniques which include GIS, Environmental Impact Assessments (EIAs), and algorithms (Torres et al., 2016). ERAs are normally performed with laboratory or field data and models to produce quantitative and qualitative decisions, particularly framed as the impact human activity has on the environment (Environment Agency, 2013; Torres et al., 2016). These can be suitable for producing a detailed holistic overview of the effects of the engineering technique on the surrounding environment where data is generally accessible.

Most risk assessments in the oil and gas industry have focused on safety analysis and risk reduction at offshore operations (Aven et al., 2007; Chen and Fu, 2003; Khakzad et al., 2013; Skogdalen and Vinnem, 2012; Vignes and Aadnoy, 2010; Vrålstad et al., 2019), which present a different set of risks to onshore and even to unconventional versus conventional oil and gas development. There is a requirement for assessing a new set of risks which offshore risk assessments are lacking and this could be best tackled using a variety of risk assessment methodologies.

Fuzzy logic approaches to risk assessment have recently been successfully used in the offshore oil and gas industry (Hu et al., 2012; Lavasani et al., 2011; Liu et al., 2013) and other fields of research (Ahmadi et al., 2016; Lavasani et al., 2015; Mirzaei et al., 2015; Sadiq and Rodriguez, 2004) to mitigate problems associated with conventional probabilistic risk analysis (i.e. when there is a lack of data to quantify the failure of components or individual contamination pathways). Here, fuzzy set theory allows the evaluation of risk using multiple types of information such as linguistic data, expert opinions, and probabilistic data to quantify pathways which are often ignored due to a lack of data. For example, studies have focused on physical equipment failure, operational risks, and some human intervention (Hu et al., 2012; Liu et al., 2013). A recent study has used fuzzy methods to evaluate the risk of seismic hazards during hydraulic fracturing operations which has taken into account huge raw data sets and expert assessment and opinion (Hu et al., 2018). The fuzzy comprehensive evaluation method used has allowed the authors to evaluate complicated influencing factors which would otherwise require complex numerical models with significant assumptions. Additionally, the model has demonstrated a successful application to a site in China and although some subjectivity exists in the expert assessment, the model demonstrated stability under sensitivity analysis. However, to date fuzzy set theory has not broken down more complex ideas such as cement failures or location of leaks in the context of petroleum well integrity, despite significant potential to provide insights for risk assessment.

Onshore risk assessments for unconventional gas development have been developed recently as quantitative or qualitative studies. However, successful quantitative studies lack a generic approach with many only focusing on the Marcellus Shale, or particularly large shale resources in North America with already heavy exploitation. Future onshore developments cannot be easily assessed prior to drilling. Additionally, specific stages during hydraulic fracturing are not considered as individual risk events even though each stage brings with it different magnitudes of risk. Groundwater contamination is a well-known concern in the onshore industry but is often poorly quantified and only site specific. Alternative methods need to be used to develop a risk assessment for onshore development which can be applied to more than one area and which focuses on independent stages of hydraulic fracturing to assess specifically where high risks to groundwater might lie.

The aim of this research is to apply fuzzy logic techniques to onshore, hydraulically fractured wells during the high-pressure well injection stage; an aspect commonly neglected due to its short, limited duration. Event Tree Analysis (ETA) and Fuzzy Fault Tree Analysis (FFTA) are adopted in this paper to develop a quantitative risk assessment framework. The novel features of this research include developing an event tree for a generic hydraulically fractured well, developing fault trees, and using FFTA to quantitatively analyse cement failure and comparing probabilistic and fuzzy fault tree methods to support this approach.

The framework developed which combines ETA and FFTA has been applied to a case study in British Columbia (BC), Canada; a region of historic and extensive conventional and unconventional onshore development, hosting approximately 25,000 energy wells for which 0.6% have been identified as exhibiting gas migration (Cahill et al., 2019). Subsequently, the Canadian context is compared with a hypothetical case study in the UK, where there is a potential future for the industry, to obtain intuitive outcomes for the probability of groundwater contamination due to gas migration from well integrity failure during well stimulation.

2. Risk assessment methodology

The focus of this research is on the pathways which can lead to groundwater contamination during the well stimulation stage of high-volume hydraulic fracturing, focusing on horizontal wells drilled into shale formations. In this paper, where /stage is defined as a unit of probability, this is always referred to as the injection stage; it can be read as "per injection stage" for clarification. Conceptual models are required to understand the barriers preventing migration and are used to understand the potential pathways by which gas could reach aquifers. Event trees are then developed using the source of the leak as the initiating event. Subsequent failure events involve well component failures whilst considering geological surroundings. These pathways and conceptual models have been developed from literature analysis, industry data and expert discussion.

2.1. Conceptual models

Various incidences of gas or fluid migration into groundwater or the atmosphere have been reported in the US and Canada over the last 50 years with significant variation in incidence rate (Bachu, 2017; Jackson et al., 2013; Lackey et al., 2017). To understand these variations in probability of gas migration occurrence, two conceptual models for a well stimulation event have been developed (Fig. 1); 1) A case study of a leaking onshore well from BC in Canada (Fig. 1a) and, 2) a hypothetical well construction often used offshore in the UK industry and in some states in the US (Fig. 1b).

Both conceptual models involve two sets of casings (a surface and production casing) and fully cemented annuli to the surface. The number of casings, depths or heights of the casings, and amount of cement used varies based on local regulations, the age of the well, geological surroundings, economic constraints, and engineering considerations.

The three geological zones identified in Fig. 1 are implemented to distinguish between three different locations where a leak could occur from the external well casing to a formation to produce a different outcome. It is expected that during well stimulation the pressure will be much greater inside the wellbore compared to the surroundings. Stimulation pressures for the case study well (Fig. 1a) range from about 57,000–62,000 kPa and the initial reservoir pressure is around 45,000 kPa. As a general assumption, fluids and gases will only move where there is a pressure gradient from a region of high-pressure to low-pressure. Additionally, in this paper the wellbore pressure at a certain depth x is defined as the well injection pressure at the surface plus the hydrostatic pressure at the same depth x. Geological zone A is defined as a lower pressure formation compared to the wellbore pressure at the same depth, zone B is defined as a higher pressure formation relative to zone A encouraging vertical migration rather than horizontal, and zone C is defined as a shallow lower pressure formation compared to the wellbore pressure at the same depth (similar to A) where a useable aquifer is potentially present. Table 1 exhibits the properties each of these zones might take.

Scenario 1 uses a specific case study from BC, Canada which has been applied for the purposes of developing a fuzzy logic risk assessment based on an example well located in the Montney resource play of NE BC, Canada (Fig. 1a). Gas migration has been reported to the regulator (BC Oil and Gas Commission; BCOGC) at this well based on field observations at the ground surface around the wellhead. As the leak was seen close to the wellhead, it can be assumed this was due to gas migration along a casing as opposed to fracture propagation or fracture connection through underlying strata. However, the underlying cause(s) of gas migration at this well have not been investigated as part of this research. Nonetheless, the case study has been used as a realistic starting point for model development. Additionally, the presence or characteristics of any aquifer systems around or intersected by this well have not been confirmed but may still exist (Cahill et al., 2019; Hickin et al., 2008). This paper focuses on shallow groundwater contamination and therefore a shallow aquifer is conceptualized within the confines of the surface casing and surface casing cement (Fig. 1a, geological zone C). As the gas migration was recognised at the surface it is possible that migrating gas is passing through or into a potential shallow aquifer system.

In terms of subsurface gas source zones, as well as the Montney formation, the Doig and Phosphate intersecting the well are considered secondary targets for gas production and will represent over-pressured gas

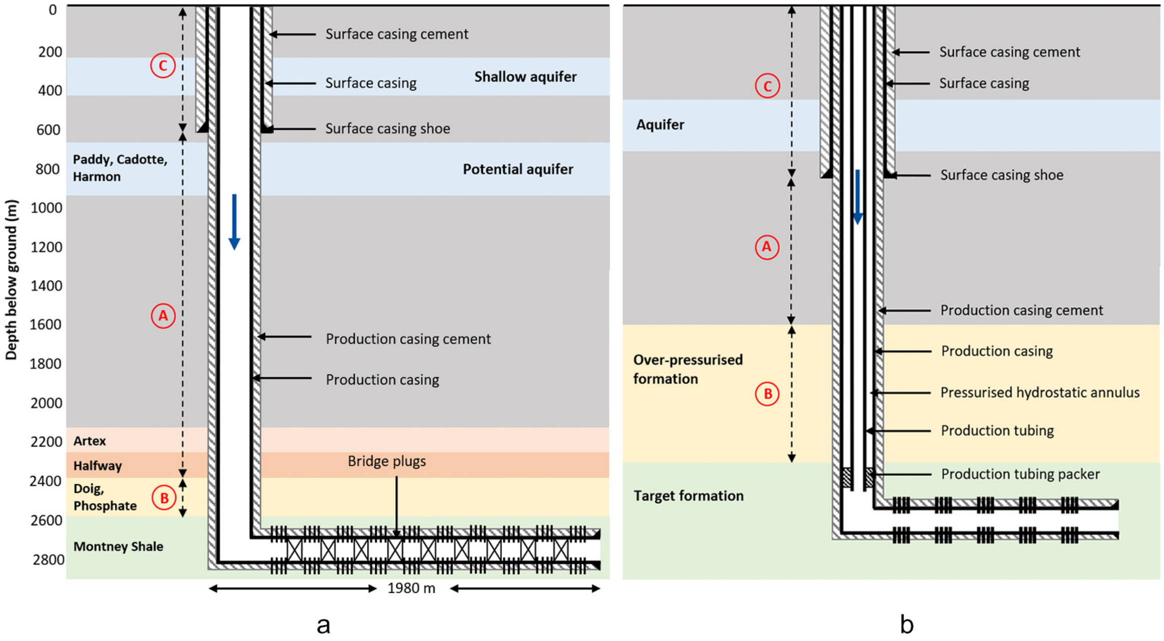


Fig. 1. Conceptual models of two different well constructions for a stimulated hydraulically fractured well. The letters correspond to different geological zones which have an effect on the pathways of contamination; A) non-gas bearing, permeable formation, B) gas-bearing, higher pressure formation (relative to zone A), and C) shallow region with a potentially useable aquifer. a. Scenario 1: A hydraulically fractured well in BC, Canada where injection occurs down the production casing. The Montney Formation is the target shale being fracked and the well has evidence of gas migration at the surface. b. Scenario 2: A potential UK well construction diagram (or sometimes seen in North America) where injection occurs down the production tubing and a packer is used to hold the tubing in place and create a pressurized annulus as an added barrier.

formations with respect to the target formation. Other formations intersecting the well, the Artex and Halfway, are sampled as containing gas but of fairly poor shows but could also represent an over-pressured gas formation with respect to the target formation. Between the Artex and Harmon lie approximately 1000 m of various formations mainly consisting of sandstone, shale, siltstone, and dolomite. These are taken as being mixed porosities and permeabilities with no gas shows but are inferred to contain formation fluids. This geological structure is common in sedimentary basins allowing for a more generic case study application.

Fig. 1a indicates a multi-stage frac has occurred with the use of bridge plugs in order to frac ten different sections of the horizontal well production casing. This is also indicated in scenario 2 (Fig. 1b) but without the addition of the bridge plugs, for simplicity.

2.2. Event tree development

Two event trees were developed using contamination pathways from both conceptual models. A main source of fugitive gas during well stimulation is from inside the wellbore to geological surroundings due to well integrity failure. Well integrity failure leading to groundwater contamination is the primary concern in this research where well barrier failure is the failure of individual or multiple barriers eventually leading to integrity failure (Davies et al., 2014). The initiating event for the event trees is the primary barrier failing as it directly experiences very high injection pressures. This will either be the production casing for Fig. 1a or the packer or tubing for Fig. 1b. The corresponding event trees for these two scenarios are indicated in Fig. 2.

In between the initiating event and outcome, events are developed based on barrier failures in the well and the difference in pressure gradients leading to each consecutive event. Table 2 gives details of each event in the event trees.

Table 1
Typical geological zone descriptions which could be expected throughout the depth of a hydraulically fractured well.

Geological zone	Formation pressure	Description
A	Formation pressure < wellbore pressure at same depth	Mixed porosities and permeabilities. Rock type: e.g. sandstone/siltstone. Contains formation fluids e.g. saline water.
B	Formation pressure > formation pressure at zone A	Tight porosity and low permeability. Gas present but unlikely economically viable. Over-pressured due to gas and hydrostatic pressure.
C	Useable groundwater zone Formation pressure < wellbore pressure at same depth	Potentially high permeability and high porosity aquifer zone. Rock type: e.g. limestone/sandstone. Potable or slightly brackish water for anthropogenic use.

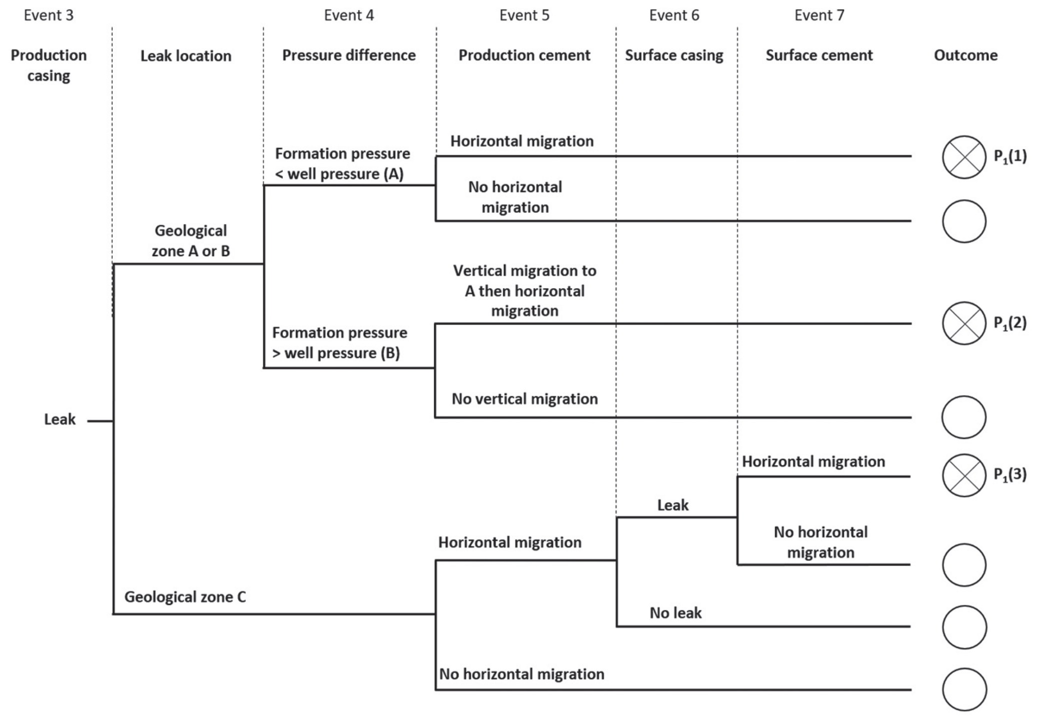
2.3. Event tree analysis

As detailed in Table 2, each individual event is quantified using different methods to obtain individual probabilities. These are quantified using either quantitative industry probability failures or, where probability failures are not possible to obtain, fault trees are constructed to obtain simpler basic events. These basic events are quantified using either quantitative industry and literature values, or qualitative expert judgement. Fuzzy logic analysis is applied in the case of expert judgement (known as FFTA) and discussed further in Section 2.6.

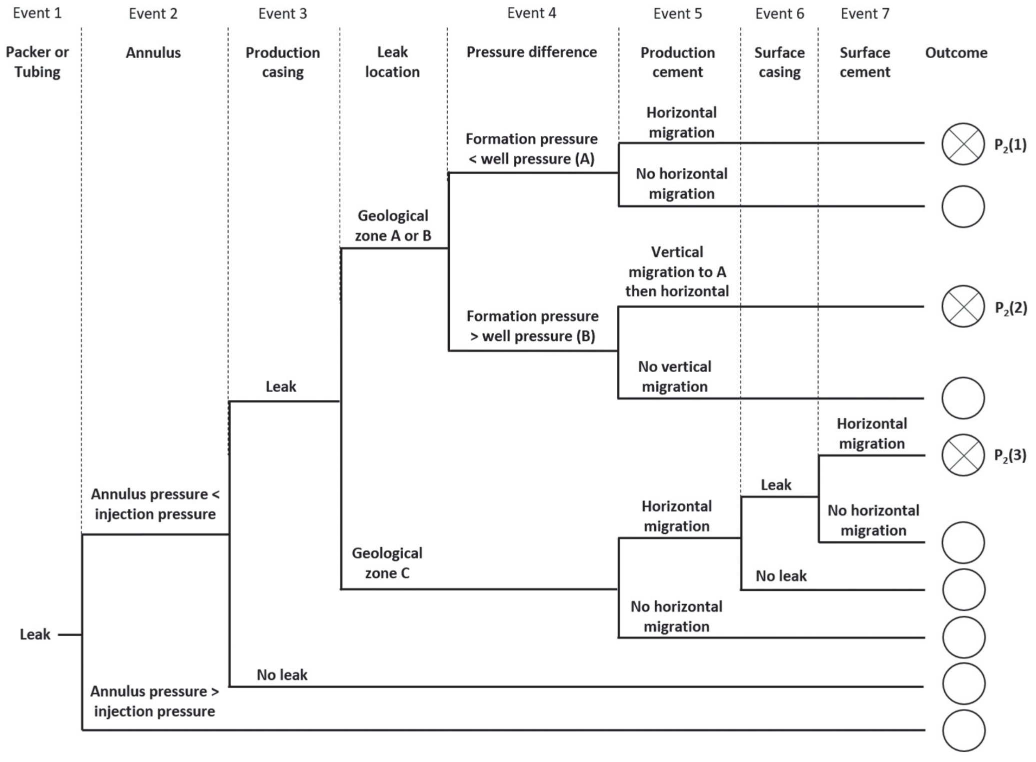
Using ETA, individual probabilities are multiplied along the event tree branches to determine a probability of groundwater contamination for each failure outcome. Both scenario 1 and scenario 2 demonstrate three individual failure outcomes which are evaluated independently.

2.3.1. Industry probability failures

Events 1, 3, and 6 are quantified using industry probability failures (Table 2). Probability failures for components of a well are obtained from the WellMaster database which contains failure data for offshore oil and gas well components, or the literature (Rish, 2005). The review conducted for this study indicated that easily accessible databases that include specific attributes pertaining to probability failures of well components, including cement, are limited to offshore wells, and similar



a. Scenario 1: Production casing leak event tree.



b. Scenario 2: Tubing or packer leak event tree.

Fig. 2. Two event trees for gas leakage into groundwater during well stimulation. The probability of failure outcomes are defined as $P_x(y)$ where x is scenario 1 or scenario 2, and y is outcome 1, 2 or 3. a. Scenario 1: Production casing leak event tree. b. Scenario 2: Tubing or packer leak event tree.

Table 2
Details of individual events within both event trees including how their probabilities are quantified. FP = Formation Pressure, WP = Wellbore Pressure. *The database used to gather well component failures indicated no failures occurred over experiment times for surface casings. Therefore, the median probability failure value was taken from Rish (2005) where it was calculated used a Poisson probability distribution.

Event/barrier failure	Scenario	Description	Quantitative probabilities
Event 1 Packer or tubing failure	2	• Initiating event in scenario 2 (Fig. 1b)	Industry values (Appendix A; Table A.1)
Event 2 Annulus failure	2	• Pressurized annulus between production tubing and casing. • Failure when pressurized annulus < injection pressure.	FFTA (probabilistic and fuzzy, Sections 2.5 and 2.6)
Event 3 Production casing failure	1 and 2	• Initiating event in scenario 1 (Fig. 1a)	Industry values (Appendix A; Table A.1)
Event 4 Pressure difference	1 and 2	• Determines direction of gas migration. • FP < WP, gas migration to outside. • FP < WP, vertical migration upwards to surface or region of lower pressure.	
Event 5 Production casing cement failure	1 and 2	• Barrier to support production casing. • Failures in the cement can occur in either the horizontal or vertical direction.	FFTA (Section 2.6)
Event 6 Surface casing failure	1 and 2	• Second casing barrier to protect groundwater.	*Industry values (Appendix A; Table A.1)
Event 7 Surface casing cement failure	1 and 2	• Barrier to support surface casing. • Failures in the cement can occur in either the horizontal or vertical direction.	FFTA (Section 2.6)

data for onshore wells was not readily available through database searches. Therefore, it is assumed for this study the offshore probability failures are similar to onshore failure rates as well construction is very similar whether onshore or offshore (The Institute of Materials Minerals and Mining, 2016). Where more accurate failure rates are obtained, event tree calculations can be updated. The data for the well components used in this paper and the explanation for obtaining the failure rates are detailed in Appendix A.

2.4. Fault tree development

Three fault trees have been developed to allow quantification of events 2, 5, and 7 (Table 2) which require more detailed analysis. The difference in pressure between the annulus and wellhead injection pressure (event 2) is quantified using a fault tree developed by Rish (2005) and is shown in Fig. 3, with an explanation for reading fault trees in Appendix B.

Two new fault trees are constructed in this paper for cement failure with the top event being either production of horizontal pathways in the cement (Fig. 4a) or production of vertical pathways (Fig. 4b). These fault trees were developed from a literature analysis (Bonett and Pafitis, 1996; Brufatto et al., 2003; Dusseault et al., 2000) and discussed with academic and industry experts within Canada and the UK. These fault trees are developed based on some subjectivity and therefore can be adjusted where reasonable explanations and evidence have been given. The explanation for these fault trees is presented below.

Failure pathways in cement were considered to occur horizontally or vertically. Horizontal failures could develop either over time from external stresses and interactions, or due to poor initial construction and placement which leads to fractures and channels developing as the cement sets (Bonett and Pafitis, 1996). Premature gelation involves a sudden increase in cement viscosity quicker than expected (Frigaard, 2018). This can lead to a loss of hydrostatic pressure control, opening

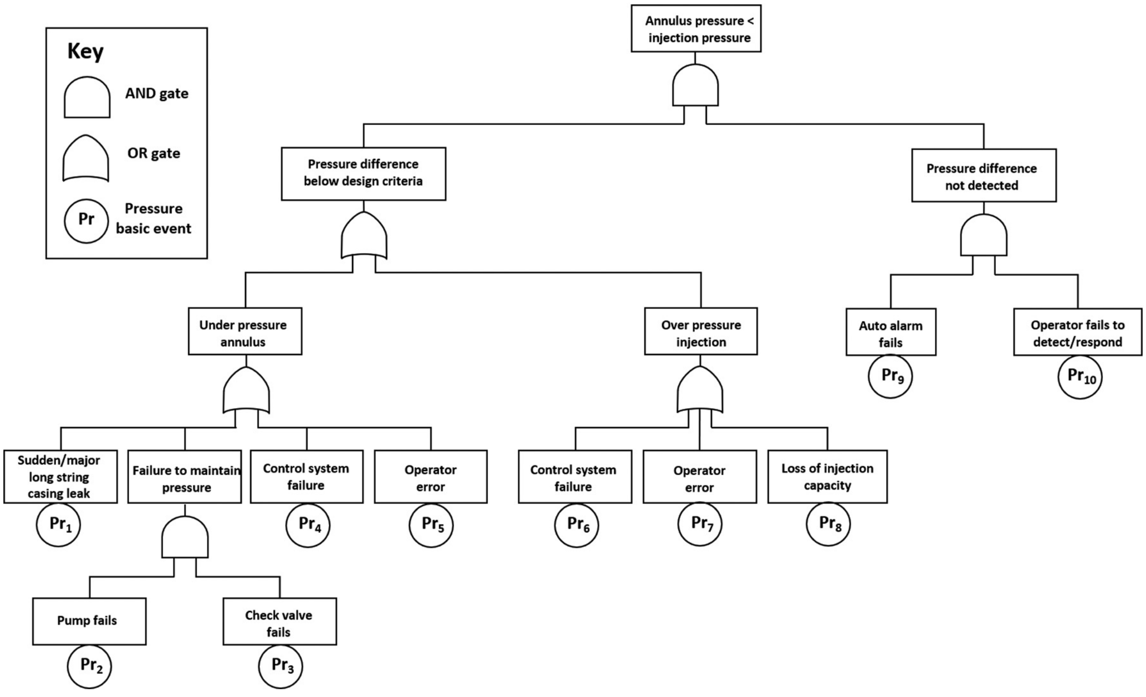
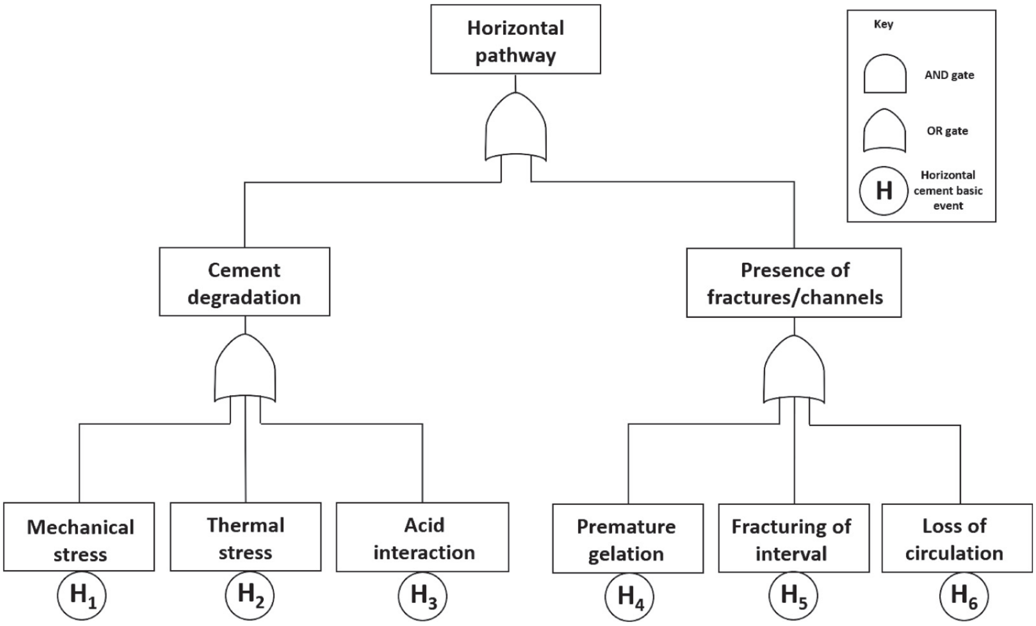
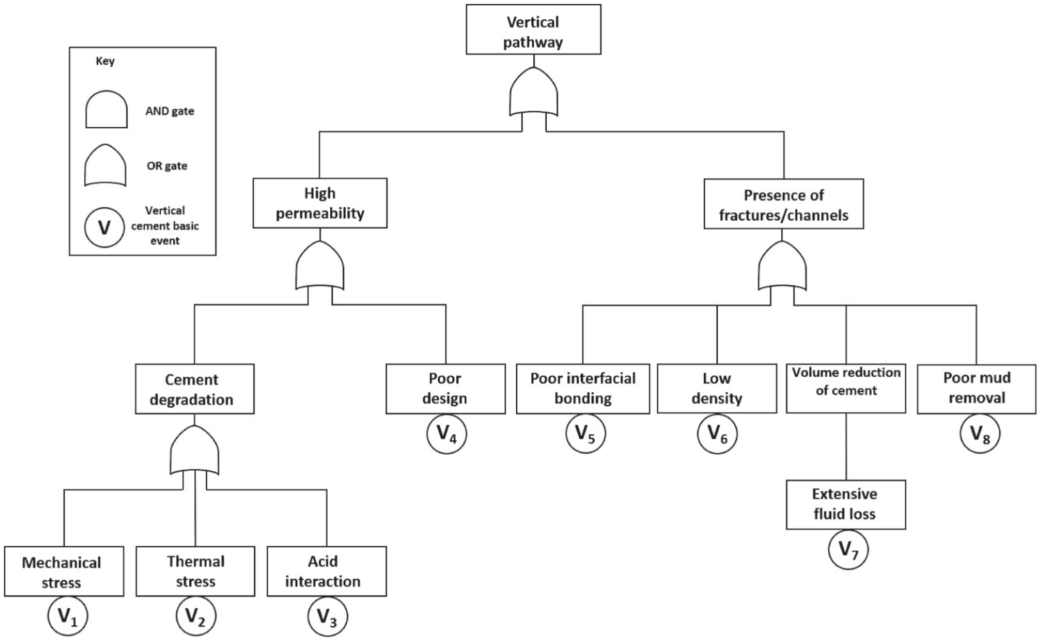


Fig. 3. Fault tree for the breach of the pressurized annulus when the wellhead injection pressure exceeds the annulus pressure (Rish, 2005).



a. Horizontal cement pathways.



b. Vertical cement pathways.

Fig. 4. Fault trees for the development of pathways causing a failure in the cement. a. Horizontal cement pathways. b. Vertical cement pathways.

a horizontal pathway (Bonett and Pafitis, 1996). During cementing placement, if fluid densities are too high there is a risk of losing cement slurry into the surrounding formation causing a loss of circulation within the borehole or fracturing of a rock interval (Bonett and Pafitis, 1996). A loss of cement could open up horizontal channels in the cement before it has set.

Vertical pathways in the cement can also develop from external stresses (Stormont et al., 2015) and interactions or poor cement design, leading to high permeability pathways allowing gas to migrate upwards (Dusseault et al., 2000; Stormont et al., 2018). Additionally, vertical fractures and channels can be developed from poor construction and placement through slightly different mechanisms. A low density slurry during cementing can lead to poor hydrostatic imbalances and vertical pathways. If mud during drilling is not removed properly, gas channels can develop between the cement sheath and rock formations or casings (Dusseault et al., 2000; Frigaard, 2018). Similarly, poor bonding of the cement can lead to channels between the cement-casing or cement-formation interfaces (Bonett and Pafitis, 1996; Stormont et al., 2015). During the cement setting process, fluid is lost but if this occurs too quickly or too much, the volume of the cement is reduced significantly to open up available space for gas to enter (Frigaard, 2018).

2.5. Fault tree analysis

Fault Tree Analysis (FTA) requires quantification of the basic events created during fault tree development. This refers to basic events Pr_1-

Pr_{10} (Fig. 3), H_1-H_6 (Fig. 4a), and V_1-V_8 (Fig. 4b). Appendix B details further information on generic FTA and an understanding on Minimal Cut Sets (MCS) in FTA. In conventional FTA, the basic events are determined using industry and literature data. The pressure fault tree (Fig. 3) can be quantified using industry data as this data does exist for all the basic events. The top event was calculated by Rish (2005) as 6.48E−11/day using probabilistic distributions. Further information on this fault tree and the distributions used are detailed in Appendix B.

2.6. Fuzzy fault tree analysis

Where quantitative data cannot be obtained to quantify event tree branches or fault tree basic events, qualitative information is used in the form of linguistic descriptors. Both fault trees in Fig. 4 require expert judgement to calculate the basic events as there is no industry data due to the subjective and ambiguous nature of cement failure. As linguistic descriptors are used instead of probabilistic values, the basic events in this case are considered fuzzy. Therefore, FFTA is required to quantify both cement fault trees. This involves the Similarity Aggregation Methodology (SAM) (Appendix C) to aggregate each opinion and numerically evaluate the basic events. Additionally, the pressure fault tree (Fig. 3) was analysed using FFTA in this research as well as FTA to compare the difference between a probabilistic method and a fuzzy method.

2.6.1. Linguistic probability levels

The linguistic terms are defined based on the probability of occurrence during the individual stage of the well. Experts from the UK and Canada independently populate each basic event for all three fault trees with a qualitative descriptor, using their expert judgement. Further information on the linguistic terms used in this research and their relationship to fuzzy membership functions is given in Appendix D.

2.6.2. Expert opinion elicitation

The opinions of experts using qualitative, linguistic information are employed to obtain information on the basic events of the three fault trees discussed in this paper. Experts with the required skill set give their own judgement on individual basic events. These judgements will vary depending on their background so a weighting system is used to account for these variations in decision-making. The weightings are calculated based on professional or academic title, length of time in profession, education level, and age, as indicated in Table 3. It is expected as an expert becomes older and increases their time in their profession, they will become more experienced. Hence, as service time and age increases so does their weighting. Equally, it is assumed as one spends more time in education understanding the technicalities and scientific understanding of cement failure, they have a more specific understanding compared with those with a broader knowledge in industry. Therefore, as education level is advanced and your academic title is increased, so does the weighting. However, if certain weightings are deemed incorrect for a specific analysis, these can be altered easily with sufficient reasoning. Appendix D details the calculated weightings of the experts used in this research.

Table 3
Weighting attributes for experts.

Category	Classification	Weight
Professional or academic title	Professor	5
	Postdoc	4
	Graduate	3
	Engineer	2
	Technician	1
Service time (yrs)	≥30	5
	20–29	4
	10–19	3
	6–9	2
	≤5	1
Education level	PhD	5
	Masters	4
	Bachelors	3
	Higher National Diploma	2
	School level	1
Age (yrs)	≥50	5
	40–49	4
	30–39	3
	21–29	2
	<21	1

2.6.3. Similarity aggregation methodology

Once each basic event has been populated with linguistic descriptors converted into fuzzy numbers, aggregation of the basic events is conducted using SAM, developed by Hsu and Chen (1996). This method is detailed in Appendix C. Aggregating expert opinions outputs a Fuzzy Possibility Score (FPS) rather than a fuzzy probability score. It is impractical to expect an expert to directly determine the probability of failure so terminology such as the possibility of occurrence of a basic event is used (Lin and Wang, 1997).

After aggregation using SAM, defuzzification is used to convert fuzzy values to a crisp possibility output using the centroid defuzzification technique. The defuzzified possibility values are finally converted to probabilities failures using a method developed by Onisawa (1988). These are both detailed in Appendix C.

2.6.4. Sensitivity analysis

FFTA provides a probability of the top event, but there is still a need to evaluate the effects each component has on the system. It is important to understand the contribution each basic event has to the top event. Sensitivity analysis can help decide the weakest components and the improvements to be made (Zhou et al., 2015). In this paper, three importance measures are used to understand the system. The Fuzzy Weighted Index (FWI) is used to determine the contribution each basic event has to the overall system to investigate alternatives or improvements. Probabilistic importance (Birnbaum's structural importance) is the “probability that the system is in a state where a particular component is critical” (Cobo, 1996). Criticality importance is the “probability that event *i* has occurred and is critical to system failure” (Cobo, 1996). A detailed description of these can be found in Appendix B.

In addition, a sensitivity analysis was conducted on the fuzzy logic model to demonstrate the sensitivity of the outcomes with respect to the input expert opinions in order to demonstrate the robustness of the approach and where variability might lie within the model. A comprehensive adjustment of the expert opinions was conducted by varying the expert inputs by +/-1 fuzzy membership level input. For example, where an expert gave an opinion of ‘low’, the input was adjusted to ‘very low’ and ‘medium’, accounting for an upper bound sensitivity (‘medium’) and a lower bound sensitivity (‘very low’). This was conducted under three scenarios, looking at all possibilities of changing: 1) one expert opinion per fault tree, 2) two expert opinions per fault tree, and 3) three expert opinions per fault tree. Table 4 demonstrates

Table 4
Number of simulations run under three different sensitivity analysis scenarios.

Fault tree	Scenario	Number of possible combinations	Number of simulations
Horizontal cement	1	60	25
	2	3480	2920
	3	194,880	149,460
Vertical cement	1	80	37
	2	6240	5778
	3	474,241	422,250
Pressure	1	80	31
	2	6240	4908
	3	474,241	330,096

all possible combinations of altering expert inputs within the three different scenarios for each fault tree. Under some circumstances, the fuzzy membership input could not be adjusted if it was already at its lowest or highest level. The outputs where this occurred were removed from the sensitivity analysis with the actual number of simulations shown in Table 4. Additionally, a brief analysis of the agreement between expert opinions was conducted on the current data set as another form of sensitivity to indicate how much expert opinions might vary.

3. Results and discussion

3.1. Fuzzy fault tree analysis results

An understanding of potential gas migration through well integrity failure in two different well construction scenarios is analysed using ETA and FFTA. FFTA is used to quantify events 2, 5, and 7 (Table 2) where linguistic terminology (Appendix D) is used by experts to populate each basic event in the fault trees. In this research study, seven experts in total were used; their calculated weightings are detailed in Appendix D. Three of the experts are academics working specifically in the area of cementing practises in deep horizontal wells. Four experts are industry-based engineers or geologists working in the oil and gas industry, managing engineers. The pressure fault tree requires expert knowledge in understanding how pressures can change during well stimulation. Two out of the original five experts with extensive drilling engineering knowledge were used for this fault tree and two more were contacted for a complete analysis of the pressure fault tree. The cement fault trees required expert knowledge in cementing practises which was the research focus of the three experts working in academia and both original engineers have extensive knowledge in this area.

Final results for all three fault trees are obtained using the SAM (Appendix C) where expert opinions are aggregated, defuzzified, and then converted into probability failures. Details of the FFTA results for each basic event are given in Appendix E and the overall top event probabilities for horizontal cement P_{HC} (TE), vertical cement P_{VC} (TE), and annulus pressure P_{Pr} (TE) are 8.36E−3/stage, 3.42E−2/stage, and 1.29E−9/stage, respectively.

Validating the top event of the cement fault trees is a challenge as very little exists on alternative methods for quantifying cement failure. Cement failure is well detected during drilling and injection but probability of failure is often unknown (Calosa et al., 2010; Considine et al., 2013). However, incidences of gas migration indicate vertical cement failure is more likely than horizontal cement failure (Dusseault et al., 2000). The results in this paper indicate the cement tree top event for vertical failure is 10 times more likely than horizontal failure.

Vertical cement migration has been quantified in some instances in previous literature. An example used here is comparing it with a Poisson distribution conducted by Rish (2005). The outputs showed a median value of 6.00E−6/day (2.40E−5/stage) with a lower and upper bound of 2.00E−6/day (8.00E−6/stage) and 1.00E−5/day (4.00E−5/stage), respectively. Using expert opinions, vertical cement migration has been quantified using FFTA and the outputs showed a value of 3.42E−2/stage, a probability $>$ 1000 times more likely than indicated by Rish (2005). There is no indication of further research conducted to quantify the failures of cement during oil and gas drilling and therefore little data is available to support or refute these methods. However, the fuzzy fault tree values have been supported by expert opinion, a part of validation of the method using industry knowledge. The horizontal cement fault tree failure probability was calculated as 8.36E−3/stage but there is no information to compare this value to. FFTA can be a new method for dealing with these gaps in the industry.

3.1.1. FFTA sensitivity analysis

The first stage of the sensitivity analysis focuses on the specific impact of the individual basic events of each fault tree on the overall top event of each fault tree. In Fig. 5, each basic event for each fault tree is plotted according to its failure probability and FWI. This demonstrates for failure probability, loss of injection capacity, Pr_8, is the biggest contributor to the top event failure probability for annulus pressure. H_4, premature gelation and V_8, poor mud removal, are the biggest contributors to the top event failure probability for horizontal and vertical cement failure, respectively.

The FWI follows a similar pattern to the failure probability in most cases (Fig. 5) but determines to what degree the top event is improved

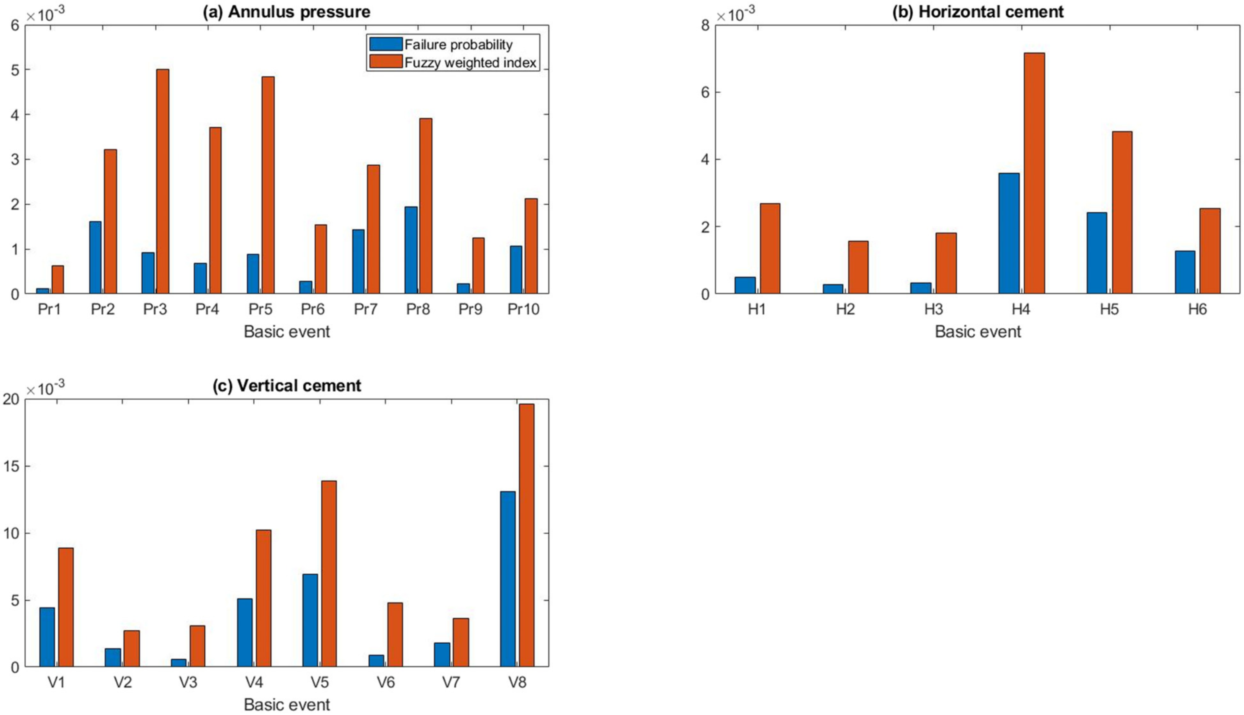


Fig. 5. Sensitivity of each basic event in the pressure and cement fault trees with respect to failure probability and fuzzy weighted index.

if each individual basic event is removed. In both cement failure fault trees, H_4 and V_8 are still considered to have the highest impact on the top event probability. Removing both will have a significant improvement on the top event probability.

Reducing the risk of premature gelation during the cementing process is important to reduce the effect of basic event H_4 on the top event. Gelation is the process in cement setting at which it begins to solidify. If the cement sets too early this can lead to a loss of hydrostatic pressure control in the well and gas or formation fluids can enter the cement annulus leading to horizontal channels (Bonett and Pafitis, 1996). Methods to improve this can involve improved designs of the cementing process such as using casing centralizers or improved cementing mixtures (US Environmental Protection Agency, 2016).

Reducing the risk of poor mud removal during drilling is important to reduce the effect of basic event V_8 on the top event. Mud removal occurs during the drilling process when cement is used to displace the mud from the borehole. It is vital mud channels are eliminated otherwise lower yield stresses of drilling fluids could cause preferential pathways for gas migration, or water could be drawn from the mud into the cement when the two come in contact. This can shrink and dry out the mud, opening up vertical pathways along the annulus for gas to flow. Successful mud removal depends on factors such as downhole conditions, borehole characteristics, fluid rheology, and displacement design along with optimal fluid displacement (Brufatto et al., 2003). These factors must be carefully calculated to reduce the risk of vertical cement failure.

Although Pr_8 is considered to have the highest contribution to the top event according to failure probability, Pr_3, check valve fails, and Pr_5, operator error when under pressure are both considered the most sensitive to the FWI and therefore removing these errors in operation will improve the top event probability on the annulus pressure fault tree.

According to Fig. 6, the probabilistic importance and criticality importance values for basic events Pr_9 and Pr_{10} are much higher compared with the others, indicating if either of these components fail, the system will fail (Cobo, 1996). Therefore, it is vital to ensure the auto alarm system for detecting a pressure difference is tested frequently (Pr_9) and operators are aware of potential errors in their practice (Pr_{10}).

Elements of the pressure fault tree could require improvement for a more realistic situation during pressure control. It was suggested the control system failure basic events Pr_4 and Pr_6 could occur, but in reality would unlikely lead directly to an under pressurized or over pressurized system. If this occurrence was recognised, the sand would be flushed from the system and fracturing would stop, eliminating the failure probability altogether.

The second stage of the sensitivity analysis was conducted on the model framework to determine the effect of varying expert inputs on the individual fault trees and hence the overall risk output. Three models were run where the expert inputs were varied under scenarios 1, 2, and 3 with the outputs shown in Figs. 7, 8, and 9, respectively. The adjustments made to the expert inputs by +/-1 fuzzy membership function were to account for potential human error or variation in human judgement; a likely cause of varying results when using fuzzy logic methods. If the human was an expert in the field (which is a requirement for the model), it is unlikely they would have made an error in judgement by much more than +/-1 linguistic term.

In scenario 1 (Fig. 7), the tornado diagrams indicate both cement fault trees show a variation in the output by only +/-20%, where 50% of the combinations are within an error of only +/-5%. This is not a significant change to the overall top event output but indicates the error on the cement fault trees could be within +/-20%. In correlation with the sensitivity analysis conducted on the fault trees, it is evident from Fig. 7 that basic events H_4 and V_8 are the most sensitive to changes in human inputs. The annulus pressure demonstrates a much larger sensitivity with events Pr_9 and Pr_{10} (also most sensitive in the previous analysis) showing up to 150% variability. This outcome would shift the top failure event of the pressure fault tree from 1.29E−9/stage to 3.2E−9/stage. Although the error appears large, due to the very low probability of the top event failing this error has a very small impact on the overall model.

Histograms were developed in the two scenarios where more than one variable was changed i.e. where at least two expert opinions were changed per fault tree (Figs. 8 and 9). This allowed a visual representation of the population of combinations at varying sensitivities. Under both scenarios, the majority of combinations obtained an output between ±50% for the annulus pressure fault tree and between ±20% for the cement trees, indicating a similar sensitivity as demonstrated by the tornado plots. Increasing the number of changes made has not had a big impact on the sensitivity of the model but has increased the

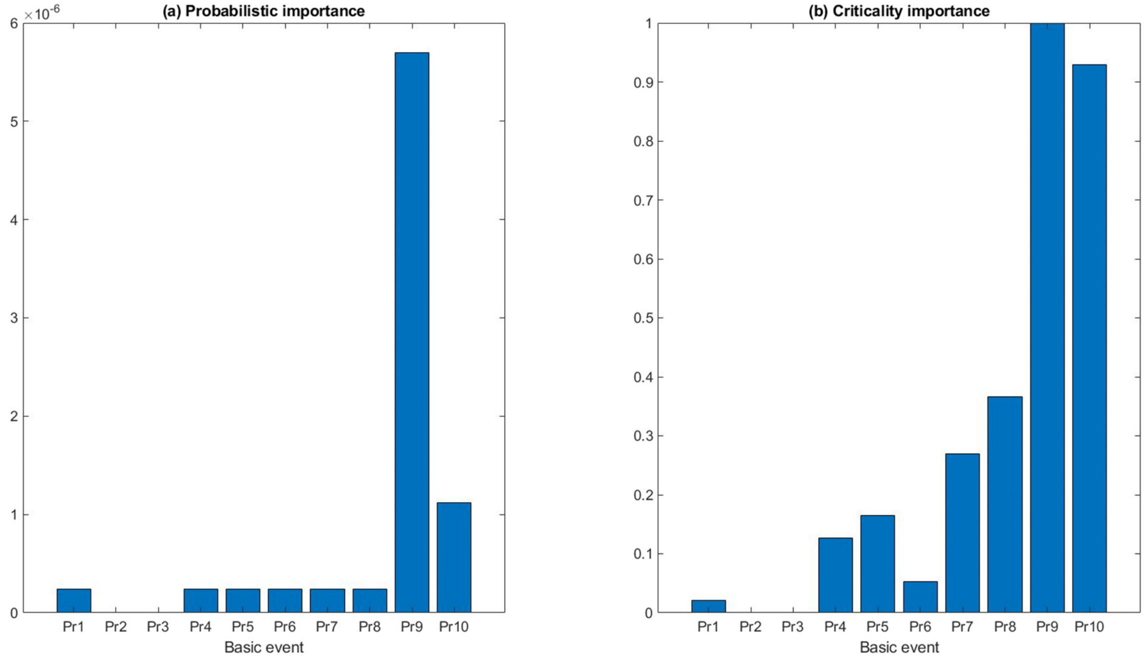


Fig. 6. Sensitivity of each basic event in the pressure fault tree with respect to probabilistic importance and criticality importance.

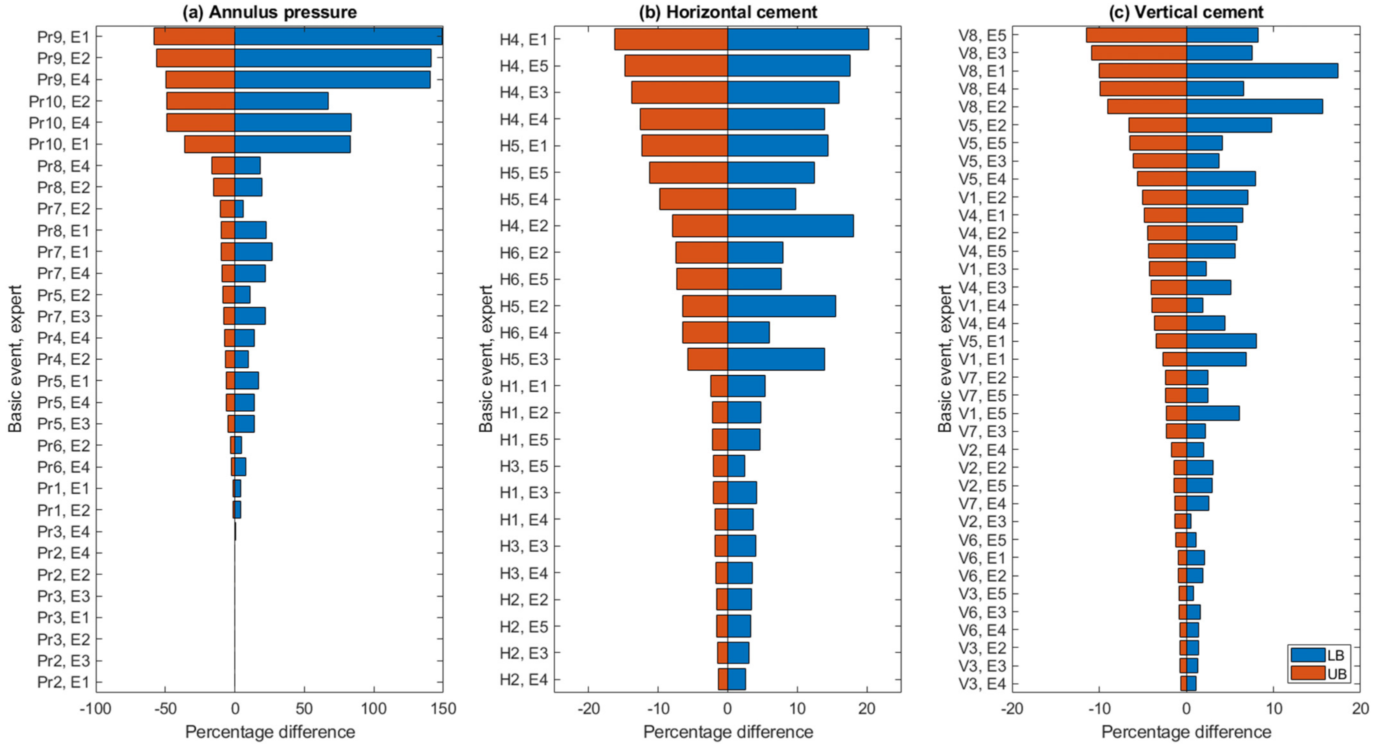


Fig. 7. Tornado diagrams indicating the sensitivity of changing one expert opinion per fault tree (scenario 1). LB: lower bound, UB: upper bound, Prx: basic event, Ey: expert opinion.

density within the ranges discussed above (Fig. 8). However, there have been a few combinations which increased the error of the top event, particularly in the annulus pressure fault tree. A few combinations (12 out of 330,096) increased the error by over 900% which increases the top event probability from 1.29E−9 to 1.3E−8. This will affect the overall system by 10 times the original assessment. However, as discussed earlier the outcome probability of the system is still extremely small, despite these rare occurrences of high errors.

The larger variabilities in sensitivity which can be seen from Figs. 7, 8, and 9 indicates a concern if different experts were chosen with differing opinions. Due to the challenge in obtaining a new set of experts in this niche field of study, this was unable to be tested to see how much

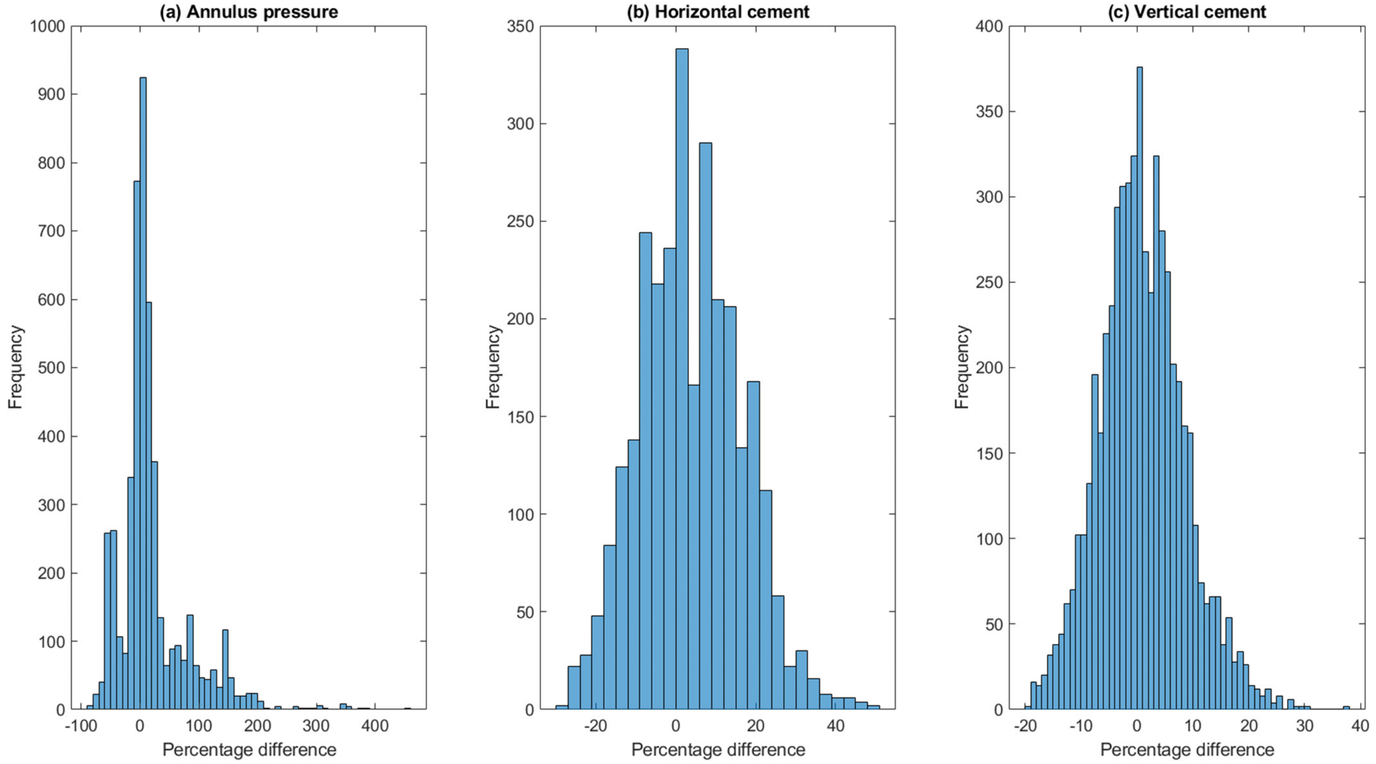


Fig. 8. Histograms indicating the sensitivity of changing two expert opinions per fault tree (scenario 2).

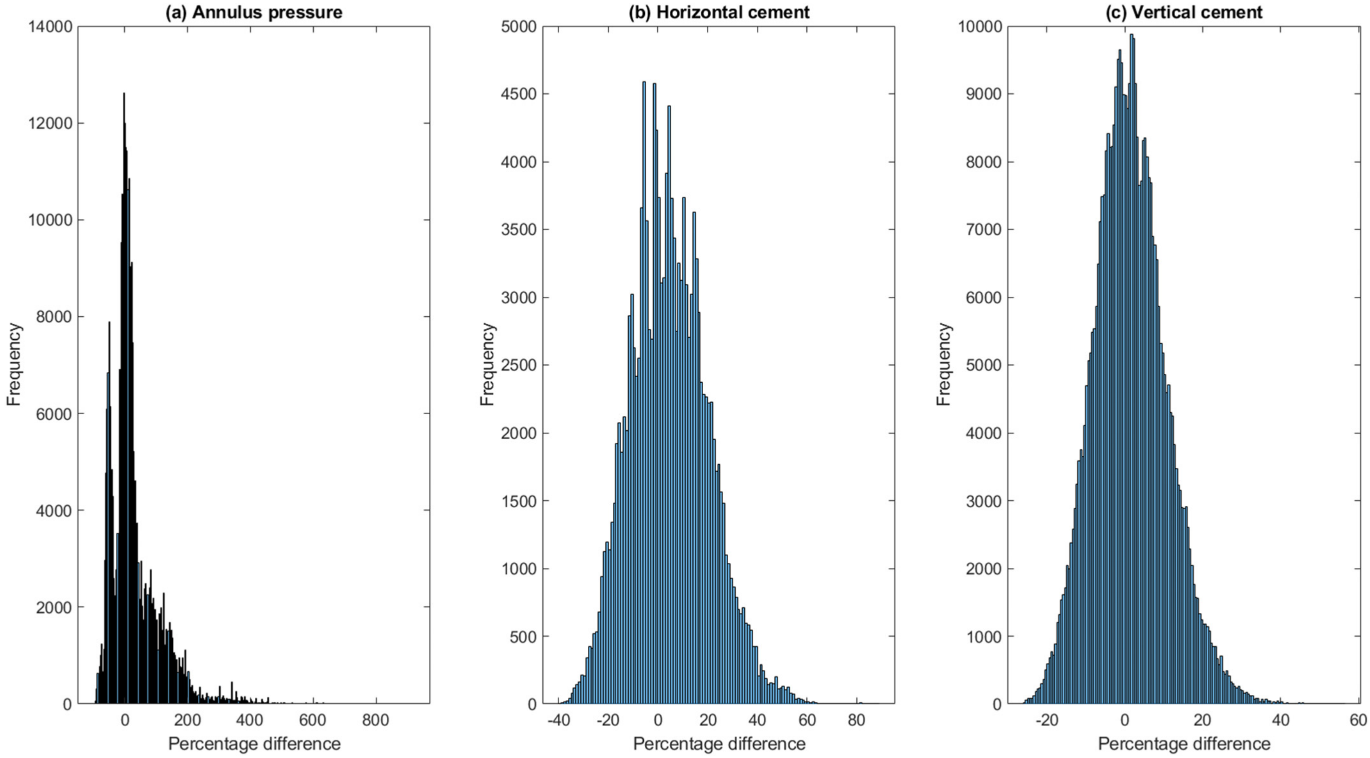


Fig. 9. Histograms indicating the sensitivity of changing three expert opinions per fault tree (scenario 3).

variability might arise. However, the agreement between the experts used in this study can be obtained to indicate how much variability might exist between experts who are completely unrelated. In this study, all experts were anonymous, living in different countries and were unaware of each other's input. The agreement between the experts is conducted from the SAM, detailed in Appendix C, Eq. C.3. The output from this agreement calculation is shown in Appendix E but the overall average agreement for each expert used in this study is shown in Table 5. The closer the value is to 1, the higher the agreement between each expert. Table 5 indicates most experts have a strong agreement across all basic events within each fault tree, with expert 1 averaging the lowest agreement in the vertical cement tree, expert 2 in the horizontal cement tree and expert 5 averaging the lowest agreement in the pressure tree.

An analysis of the expert agreements for each basic event (Table E.1) indicates H_6, V_2 and Pr_8 demonstrate the lowest agreement between experts. This suggests there could be more variability in expert inputs within these three events. As demonstrated by earlier sensitivity analysis and Fig. 7, all three of these basic events are not highly sensitive to change and therefore even with expert variability, this would not alter the result significantly.

3.1.2. Comparison of fuzzy versus probabilistic

An important element of this paper is to demonstrate the viability of using fuzzy logic methods where alternative probabilistic methods are not appropriate. Probabilistic FTA was conducted for the annulus pressure fault tree using uniform, triangular, and Poisson distributions (Rish, 2005), and a top event failure value of 6.48E−11/day (2.59E−10/stage) was obtained. Using FFTA, a value of 1.29E−9/stage was obtained, as discussed in Section 3.1. Both methods indicate a similarly low probability value for wellhead injection pressure exceeding annulus pressure, supporting the fuzzy logic methodology.

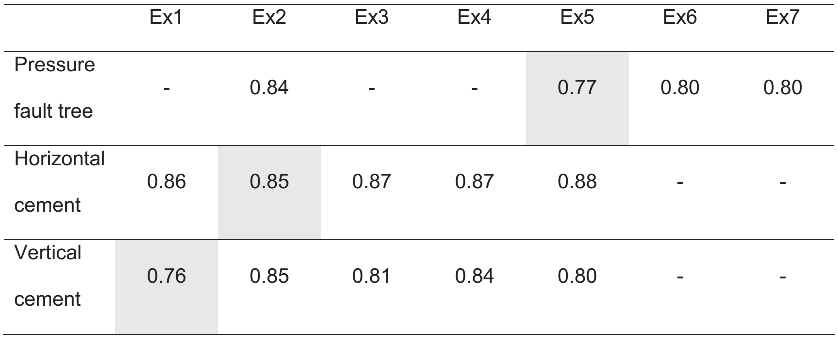
However, despite similar magnitudes the fuzzy method calculates a top event failure 5 times more likely than the probabilistic method. Analysing the failure probabilities of individual basic events helps understand these differences and where each method might represent a more realistic output (Table 6).

Fuzzy logic applications are suitable where human error might be involved. Basic events Pr_5, Pr_7, and Pr_{10} all involve an operator error. Probabilistically, human error was evaluated using a uniform distribution (Rish, 2005) based on work conducted by Swain (1987) so all human-related procedures had the same probability of failure based on the same distribution. In reality, human errors vary depending on the situation. The fuzzy method accounts for human errors based on real life experiences working specifically on hydraulically fractured wells. Each operator error leading to a different outcome used individual expert knowledge and will therefore have a more realistic probability output. Results in Table 6 indicate a difference in probability for all three operational error basic events (Pr_5, Pr_7, Pr_{10}).

The basic event Pr_1, a sudden or major long string casing leak, shows the largest difference of magnitude 100 which might affect the overall top event. This basic event is a technical failure and might be best represented as a probabilistic value if there was enough data to indicate the failure rate of the component for specific hydraulically fractured wells. However, the failure probability and FWI of this basic event is ranked lowest according to Fig. 5a indicating it has the lowest contribution to the overall system, and is not highly sensitive compared with other basic events as demonstrated by Fig. 7 and therefore not as important to the top event probability.

The fuzzy probability method has demonstrated uncertainty based on expert inputs as demonstrated by the sensitivity analysis conducted in Section 3.1.1, especially for the pressure fault tree. Although the fuzzy method is better at handling human opinion, the potentially larger errors could lead to a significantly different result. This sensitivity might affect a choice between using fuzzy or probabilistic methods. Where a large number of top experts with extensive knowledge can be used for the analysis, the fuzzy method would be preferable, particularly where human errors need to be quantified based on real experiences. However, if there are not enough experts to provide unbiased opinions, the probabilistic method could be more appropriate.

Table 5
The average agreement for each expert for each fault tree. The highlighted cells are those with the lowest agreement within that fault tree.



	Ex1	Ex2	Ex3	Ex4	Ex5	Ex6	Ex7
Pressure fault tree	-	0.84	-	-	0.77	0.80	0.80
Horizontal cement	0.86	0.85	0.87	0.87	0.88	-	-
Vertical cement	0.76	0.85	0.81	0.84	0.80	-	-

3.2. ETA results

The probability failures obtained from FFTA are applied to the event trees constructed in Section 2.2 to conduct ETA and to determine a final probability for gas migration during well integrity failure. The failure probability values for both event trees have been calculated based on the probabilistic and fuzzy inputs to the model, shown in Appendix E; Table E.2.

Two different scenarios were used based on a Canadian case study (Fig. 1a) and a likely UK well construction (Fig. 1b). Both scenarios have been assessed using fuzzy inputs calculated in this paper and probabilistic inputs calculated from Rish (2005). In both scenarios the user inputs the formation pressure and wellbore pressure in MPa of where the leaks could occur and for scenario 2, the user must input whether a packer or tubing has failed.

Different output values are obtained based on the well construction scenario and the location at which the leak has occurred (Table 7). P(1) indicates a leak at geological zone A, P(2) at geological zone B, and P(3) at geological zone C.

The ETA has been conducted using fuzzy methods as described in this paper and compared against probabilistic values for similar leaks on waste injection wells (Rish, 2005). Rish (2005) developed probabilistic values for the FTA and ETA and therefore took more assumptions for ease of calculation. The failure of cement in the horizontal direction was not considered by Rish (2005) and therefore has been neglected in the probabilistic calculations. In this study, horizontal and vertical failure of cement were quantified using FFTA for a more accurate representation.

Table 6
Comparison between probabilistic calculated values and fuzzy logic values for each basic event in the pressure fault tree.

Basic event	Failure probability/ stage (fuzzy)	Failure probability/ day (Rish, 2005)	Failure probability/ stage (Rish, 2005)
Pr_1	1.13E−4	3.00E−7	1.20E−6
Pr_2	1.61E−3	5.00E−4	2.00E−3
Pr_3	9.12E−4	3.00E−4	1.20E−3
Pr_4	6.77E−4	1.00E−5	4.00E−5
Pr_5	8.80E−4	3.00E−4	1.20E−3
Pr_6	2.82E−4	1.00E−5	4.00E−5
Pr_7	1.44E−3	3.00E−4	1.20E−3
Pr_8	1.95E−3	1.00E−4	4.00E−4
Pr_9	2.27E−4	3.00E−4	1.20E−3
Pr_{10}	1.07E−3	3.00E−4	1.20E−3
P (TE)	1.29E−9	6.48E−11	2.59E−10

The significant difference between the probabilistic calculations from Rish (2005) and this research was the horizontal cement failure. By considering the movement of fluids or gases horizontally, the probability of failure will decrease as the cement is acting as a barrier. Despite this difference, the probability values are similar for all three events across both methods. This will be due to the differences in the probabilistic failure rates of certain components compared to the industry values. Generally, the industry values have higher failure rates than those calculated using probabilistic distributions.

The comparison of results in Table 7 involves the application of probabilistic failure rates from Rish (2005) to the conceptual models (scenarios 1 and 2) developed in this paper. However, probability failures for the breach of class 1 waste injection wells were calculated by Rish (2005) where a leak above a confining zone can be compared against a leak in geological zone a (pathway P(1)) in this paper. The values calculated by Rish (2005) are compared against the fuzzy outputs from this paper. A major packer or injection tube failure where the hydrostatic annulus is breached immediately can be loosely compared against scenario 1 in this research. The waste injection well gave a failure of approximately 1.0E−8 and the hydraulically fractured stimulation well a failure of 6.4E−6. Similarly, a packer leak event or a tubing leak event can be compared against scenario 2 in this research. The waste injection well gave a packer leak or an injection tube leak of 1.0E−17 and the hydraulically fractured well gave a failure of 8.5E−20 for the packer leak and 3.3E−19 for the tubing leak. These probability of failure outcomes are very similar across the waste injection well and the hydraulically fractured well using the probabilistic method and fuzzy method, respectively. However, due to the nature of class 1 waste, there is a requirement for tight regulations and oversight to maximise the reduction in groundwater contamination due to the high consequences if this were to occur. The consequence of methane gas reaching groundwater during hydraulic fracturing is lower than class 1 waste as methane gas is technically not harmful to drinking water. This difference in regulation could impact the overall probabilities and individual components. Finally, the probabilities for class 1 waste injection were calculated across the life of the well whereas for the hydraulically fractured well, this was only

Table 7
Results from the event trees, Fig. 2, indicating the different probability outcomes for potential groundwater contamination depending on geological location, well construction, and method.

		Method	P (1) (/stage)	P (2) (/stage)	P (3) (/stage)
Scenario 1	–	Fuzzy	6.35E−6	2.17E−7	8.97E−13
	–	Probabilistic	1.20E−4	2.88E−9	1.44E−9
Scenario 2	Packer	Fuzzy	8.53E−20	2.92E−21	1.21E−26
	Packer	Probabilistic	4.97E−18	1.19E−22	1.49E−23
	Tubing	Fuzzy	3.34E−19	1.14E−20	4.72E−26
	Tubing	Probabilistic	7.46E−18	1.79E−22	2.24E−23

across the stimulation stage. This temporal difference would also alter the overall probabilities; the longer an engineered event is occurring, the higher the likelihood of potential contamination.

3.3. Sensitivity analysis

Results in Table 7 indicate a large difference in failure probability for all three contamination events between scenario 1 and scenario 2 due to less barriers in scenario 1. Production tubing is not used in scenario 1, automatically eliminating the annulus pressure barrier. The failure probability of this pressure barrier is low at 2.6E−10 or 1.3E−9 (depending on methodology). Therefore, this element of the event tree has the largest effect on reducing the probability of groundwater contamination.

Assuming any one of the three failure events occurs, the fuzzy method used in this paper indicates scenario 1 has a failure probability of 6.57E−6, and scenario 2 a failure probability of 8.82E−20 for the packer leak and 3.45E−19 for the tubing leak. If these probabilities are converted back to a fuzzy possibility, the values would be 0.08, 1.76E−3, and 1.93E−3, respectively. The linguistic terminology for these numbers fall into the category 'Very Low' which indicates the event is rarely encountered, never reported or highly unlikely during the injection stage. The outputs from this model contain uncertainty based on the fuzzy methods used, with the sensitivity analysis indicating the top event fault tree probabilities results could have an error of several hundred percent. However, even with these large errors the overall failure probabilities will still be extremely low as the magnitude will only shift by a factor of 10, still keeping the linguistic outputs as 'Very Low'.

The result of 6.57E−6 for a scenario 1 well relates to the case study of a leaking well in BC, Canada which was hydraulically fractured in the Montney formation. Within the Montney resource play, 19,337 wells have been drilled where 26 were shown to exhibit gas migration at the surface (Cahill et al., 2019), although the leaks could have occurred across any stage of the wells (e.g. drilling, production, injection, abandonment) and it is unclear what initiated the leaks. This paper demonstrates a risk assessment for a leak occurring at the production casing during well injection and gives a percentage probability of 0.0006%. It is estimated the probability of gas migration occurring in wells drilled in BC in the Montney formation is 0.13%. Although these values are significantly different, the reasons for gas migration to the surface are not necessarily from the well injection process but could have occurred during drilling, production or abandonment. Additionally, this paper only assesses risk of certain components failing related to well integrity but the risk potential increases cumulatively with the addition of other leak or migration pathways.

4. Discussion

This framework has been developed to conceptualize the migration of gas to groundwater during the well stimulation stage of a hydraulically fractured well at different points where leaks could occur. Additionally, the individual pathways have been quantified and an overall probability of groundwater contamination calculated based on a few different scenarios. This has also been compared with known data on well failures across the BC region in Canada where wells have been drilled into the Montney formation.

The failure pathways have focused on the movement of gas along wellbores where the integrity of cement and casings has failed. The movement into external formations was based on a pressure differential between the surrounding formations and the wellbore. As the well stimulation stage is when the wellbore experiences the highest pressures across the wells life cycle, it is assumed the failure of well integrity had the highest probability of occurring compared with other potential risks during this stage. Other more probable risks which were outside the scope of this work would be induced seismicity from the high pressures, leading to potential wellbore failure or fracture propagation from induced faults, and the spilling of chemicals used during the injection process, leading to infiltration into groundwater. The same methods as used in this paper can be taken for assessing these pathways to groundwater contamination which can provide a holistic understanding of many risks leading to groundwater contamination during well stimulation.

This model has taken a deterministic approach whereby it is assumed the process of injection has been 4 h and the failure of components leading to migration is within this timeframe. The model assumed once gas reached the external surroundings it would reach groundwater at some point in time, leading to the potential for contamination. This would be the case if the leak occurred at geological zone C. The movement of gas from the external formation upwards to an aquifer has not been quantified within the model as it is outside the scope of this work, but this can be added as a pathway to the event tree with a quantifiable probability of failure.

When compared to existing methods, the new framework has the following key advantages:

1. Some published quantitative models on onshore hydraulic fracturing focus on one specific pathway which requires heavy computational modelling to achieve a desired output with a degree of uncertainty. This is an inefficient process for understanding the magnitude of gas migration during hydraulic fracturing and the models are not clearly broken down into independent failure events to understand where the highest risk events occur. This new framework relies on qualitatively understanding all pathways which can lead to groundwater contamination and applying a variety of quantitative techniques to evaluate the magnitude of their failures, depending on the available data. The quantification of each event can be easily updated depending on the conceptual qualitative model without the need for heavy computation.
2. Other published quantitative models require less heavy computation but rely on historic data for a specific site to determine a probability of failure. This does not allow for a generic framework and none of these models have been shown to be applicable to other sites across the world. This framework has shown its applicability to two very different sites in the UK and Canada without the reliance on historic data. When developing a technique in a new area, such as the UK, historic data cannot be relied upon and hence generic models and frameworks are a requirement. This paper does not rely on the use of historic data but has used what is available to help compare the outputs from the fuzzy model. However, once trust exists in the model, this data is not required.
3. Qualitative models have been a useful tool in developing generic legislation and government guidelines for new onshore hydraulic fracturing sites, but these models do not allow a quantitative understanding of certain risks which the public and society see as essential to their wellbeing. This new framework presents a qualitative conceptual understanding of risk pathways but applies quantitative analysis for an improved understanding of risk to the water environment during hydraulic fracturing and can equally be applied to measure the risk to alternative receptors such as air quality, ecology and humans.

The key disadvantages of the method are as follows:

1. Incorporating fuzzy logic is a useful method for a lack of data in the oil and gas industry and where numerical data cannot replace invaluable expert opinion. However, the method originates amongst some subjectivity where large differences in opinion can exist amongst experts. This is partly resolved using the weighting system but there also exists subjectivity in the selection of weighting factors. Validating the method is a challenge to demonstrate without numerical data to compare against the expert opinions but has been shown to work well in this paper where there has been a clear comparison of FFTA versus FTA.
2. As is particularly the case for the UK hypothetical well, it is more of a challenge for experts to make intuitive decisions on potential failures in cement without a more detailed analysis on subsurface strata, including pressure measurements of important formations. Data

collection in this area presented to the experts can help to improve the accuracy of their decisions. Additionally, a deeper understanding of cement failure in general is required to extend the fault trees and with this, cement failure data can help to validate the fault tree outputs.

5. Conclusions

This paper presents a new framework for the quantitative assessment of risk of groundwater contamination from well integrity failure during hydraulic fracturing. This paper has focused on a crucial stage of hydraulic fracturing, well injection, but the framework can be easily applied to other stages during hydraulic fracturing.

The new risk framework was successfully applied to a hydraulically fractured well in BC, Canada, and a hypothetical construction in the UK. Based on the results obtained, the following key findings are summarised:

1. The new framework successfully combines the use of probabilistic failure rates and fuzzy logic to handle analysis with areas of high data certainty and those severely lacking data. ETA allows a more rigorous analysis of the pathways for contamination to occur and highlights where improved data collection is required. This framework allowed the quantification of three potential events leading to groundwater contamination during well injection with a novel idea of adding improved representation of failure by incorporating the quantification of cement failure using fuzzy logic, a topic severely lacking in data.
2. The fuzzy logic model used to combat the lack of data on cement failure was applied to cement crack propagation in both the horizontal and vertical directions to account for gas migrating either up a well annulus or horizontally into the surrounding formations. The challenges in expressing cement failures in the industry was overcome in this paper by incorporating experts to use linguistic descriptors to describe individual failure basic events as opposed to numerical values. The fuzzy logic method handled appropriately the quantification of human error and the results from the cement FFTA highlighted the importance of cement selection and the full removal of mud cuttings during drilling.
3. A novel aspect of this paper directly compared FFTA with conventional FTA using the same pressure fault tree to demonstrate and validate the strength of using fuzzy logic when suitable. The outputs from this comparison identified a similarly low final probability value from both methods, supporting the use of FFTA as a viable alternative for conventional FTA. Additionally, it was noted the fuzzy method allows an individual analysis of each human error based on real life experiences compared with a probabilistic analysis, and therefore is able to calculate a more accurate representation of human error. This novel comparison highlights the importance of combining fuzzy logic inputs, where human error plays a large part, with accurate probabilistic values to improve the accuracy of the overall probability failure.

Future work will focus on extending the framework for application to other stages of the well such as production or abandonment, where an understanding of logical failure events exists. An aggregative analysis of all stages from site setup to abandonment will serve a more accurate picture of the risks to groundwater over the lifetime of a well during hydraulic fracturing. Following this, the framework can be used to analyse more complex events which could occur during well injection. These events could involve induced seismicity caused by well stimulation leading to wellbore failure or fracture propagation caused by well stimulation, both of which could lead to gas migration. Aggregating all these events can produce a more holistic risk assessment across this stage of fracturing and equally be applied to the other stages. The work presented in this paper is conceptual but allows clear development for further research and development in the area of hydraulic fracturing and other subsurface activities.

Notation

BC	British Columbia
BCOGC	British Columbia Oil and Gas Commission
EIA	Environmental Impact Assessment
ERA	Environmental Risk Assessment
ETA	Event Tree Analysis
FFTA	Fuzzy Fault Tree Analysis
FP	Formation Pressure
FPS	Fuzzy Possibility Score
FTA	Fault Tree Analysis
FWI	Fuzzy Weighted Index
MCS	Minimal Cut-sets
SAM	Similarity Aggregation Methodology
WP	Wellbore Pressure
QRA	Quantitative Risk Assessment

CRediT authorship contribution statement

Olivia Milton-Thompson: Conceptualization, Methodology, Software, Formal analysis, Investigation, Validation, Writing – original draft, Writing – review & editing, Visualization. **Akbar A. Javadi:** Conceptualization, Resources, Writing – review & editing, Supervision. **Zoran Kapelan:** Writing – review & editing, Supervision. **Aaron G. Cahill:** Conceptualization, Investigation, Resources, Writing – review & editing, Supervision. **Laurie Welch:** Resources, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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