Geotechnical classification and Bayesian network for real time risk assessment in mining

Ritesh Kumar Mishra
Geotechnical classification and Bayesian network for real time risk assessment in mining

Ritesh Kumar Mishra

A doctoral dissertation completed for the degree of Doctor of Science (Technology) to be defended, with the permission of the Aalto University School of Engineering, at a public examination held at Otakaari 3, Espoo on 24 June, 2019 at 10:00.

Aalto University
School of Engineering
Department of Civil Engineering
Geoengineering
Abstract
Mining involves the extraction of finite resources for their use in vast number of applications. Depletion of resources over time has required mining to be carried out underground and unprecedented depths. It is therefore important to conduct geotechnical risk assessments in advance to prevent accidents and sustain economic mining operation. Extent of available geotechnical information varies for a mine as the mine progresses from feasibility to operational stage. Geotechnical risk assessment (GRA) can be incorporated into the mine planning process from as early as the pre-feasibility stage. A formal risk assessment can be planned using appropriate scope definition which can help chose from a number of risk assessment tools and parameters.

The goals of the research were: design a geotechnical risk classification system, which can be used from preliminary stages of mine planning and to motivate a detailed risk assessment; develop guidelines to prepare the scope of a detailed GRA; define selection criteria to choose the appropriate hazard identification tool and risk assessment parameters; carry out risk assessment in presence and absence of historical incident data; develop a framework to carry out geotechnical risk assessment in real time; represent and communicate the final risk to the work force for mitigation planning.

The proposed geotechnical risk classification system (GRC) can be used to identify, rank and communicate the hazardous sections of a mine to the work force. The guidelines developed for defining the scope of the risk assessment and the numerical ranking system for risk assessment parameter selection can be used to define the risk assessment process and choose between deterministic, probabilistic and empirical method of risk assessment. The demonstrated methodology of fault tree and event tree can be used to break down a hazard into its elemental causes and to plan against all possible outcomes following an incident. Bayesian network (BN) based risk assessment can be used to model complex causal relationship of accidents and carry out incident investigation using the same model. It was shown using parameter learning that normal distribution of mine incidents was a better fit for incident forecasting compared to Poisson distribution for the cases studied in the thesis. A new method to combine multiple probability distributions to forecast future incidents has been proposed. It was demonstrated that BN based risk assessment can incorporate expert opinion in absence of data to forecast incidents. Finally, the measured risk can be communicated and monitored graphically using the F-N diagram.

Keywords geotechnical risk, FN diagram, risk assessment, FTA, ETA, GRC system, Bayesian network, roof collapse
Acknowledgements

I would like to begin by thanking Gordon White, Dzikamai Gangaaidzo, Atkins Sitwala and all my colleagues at First Quantum Mining and Operations, for their support during my transition from work life to academia. I will remain indebted for the confidence you showed in me while I embarked on the journey of my doctoral studies despite the short term challenges it brought upon at work. I would like to especially acknowledge Prof. Mikael Rinne for his guidance and advice towards my doctoral studies. Despite his busy schedule, he managed to find time for overseeing my research, and provide an independent work environment where I could pursue my research ideas with complete freedom.

I wish to thank all my co-authors, Mikael Rinne, Lauri Uotinen, Mateusz Janiszewski, Topias Siren, Risto Kiuru and Martyna Szydlowska for taking time and making valuable contributions towards my publications which has paid a pivotal role towards my dissertation. I would like to show my gratitude to Otto Hedstrom for assisting me in field trips for work related to my dissertation. I would also like to acknowledge the help and guidance offered by Lauri Uotinen in helping me prepare for the doctoral studies and guide me along the way from start to finish. His patience in attending to my trivial queries and his enthusiasm and concern towards my work and research in general has been a constant source of motivation.

I had the opportunity to work with some of the smartest people I have met during my doctoral studies. I would like to extend my thanks to all my colleagues at department of civil engineering, Lauri Uotinen, Topias Siren, Mateusz Janiszewski, Harm Oosterbaan, Tuomo Hänninen, Martyna Szydlowska, Magdalena Dzugala, Enrique Caballero and Henri Munukka for their insightful discussions which made a valuable contribution towards my research. I would like to also thank Antti Peltonen, who welcomed me in his apartment in time of need and made my year long stay in Finland memorable. My gratitude goes to the entire staff of the department of civil engineering for assisting me in every step of the way throughout the course of my research.

Finally, special thanks to my loved ones, especially my wife Naomi Roe for her unwavering support and sacrifices. This thesis wouldn’t have been possible without your belief in me.

Kalumbila, 1st January 2019
Ritesh Kumar Mishra
Funding acknowledgments

The author gratefully acknowledges the following funding sources which enabled the completion of research presented in this dissertation. The research was carried out without the involvement of the funding sources and there is no conflict of interest.

School of Engineering, Aalto University
Department of Civil Engineering, Aalto University
European Commission FP7 (280855)
Academy of Finland (297770)
Contents

Acknowledgements................................................................................................................................. 5
List of Abbreviations................................................................................................................................. 9
List of Publications ................................................................................................................................. 10
Author’s Contribution ................................................................................................................................. 11
1. Introduction ........................................................................................................................................ 13
   1.1 Research problem ............................................................................................................................. 14
   1.2 Objectives ......................................................................................................................................... 16
   1.3 Scope ............................................................................................................................................... 17
   1.4 State of the art of geotechnical risk assessment ................................................................................. 17
2. Research Method .................................................................................................................................. 19
3. Preliminary risk classification for underground mines ...................................................................... 20
   3.1 Sub - classification based on mining properties .............................................................................. 20
   3.1.1 Mining Method ............................................................................................................................. 20
   3.1.2 Rock mass characteristics ........................................................................................................... 22
   3.2 Summary of classification ................................................................................................................. 25
   3.2.1 Geotechnical Hazard Potential .................................................................................................. 25
4. Preparing scope of detailed geotechnical risk assessment (GRA) ..................................................... 28
   4.1 Elements of Geotechnical Risk Assessment (GRA) ........................................................................ 28
   4.2 Hazard Identification Tools .............................................................................................................. 29
   4.3 Risk assessment parameters .............................................................................................................. 31
   4.4 Risk assessment approach ................................................................................................................ 31
   4.5 Selection of risk assessment approach ............................................................................................. 32
5. Probabilistic risk assessment using frequentist and Bayesian Interpretations .................................... 36
   5.1 Strainburst likelihood analysis using fault tree ............................................................................... 36
   5.2 Strainburst consequence analysis using event tree .......................................................................... 38
   5.3 Likelihood and consequence analysis using Bayesian network .................................................... 39
   5.3.1 Spalling depth forecasting using fault tree and frequentist interpretation .................................... 41
## List of Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>BN</td>
<td>Bayesian Network</td>
</tr>
<tr>
<td>BTA</td>
<td>Bow Tie Analysis</td>
</tr>
<tr>
<td>CPT</td>
<td>Conditional Probability Table</td>
</tr>
<tr>
<td>ETA</td>
<td>Event Tree Analysis</td>
</tr>
<tr>
<td>FMEA</td>
<td>Failure Mode and Effect Analysis</td>
</tr>
<tr>
<td>FN</td>
<td>Frequency to Number (of events)</td>
</tr>
<tr>
<td>FOS</td>
<td>Factor of Safety</td>
</tr>
<tr>
<td>FTA</td>
<td>Fault Tree Analysis</td>
</tr>
<tr>
<td>GHP</td>
<td>Geological Hazard Potential</td>
</tr>
<tr>
<td>GRA</td>
<td>Geotechnical Risk Assessment</td>
</tr>
<tr>
<td>GRC</td>
<td>Geotechnical Risk Classification</td>
</tr>
<tr>
<td>GSI</td>
<td>Geological Strength Index</td>
</tr>
<tr>
<td>MSHA</td>
<td>Mine Safety and Health Administration</td>
</tr>
<tr>
<td>NIOSH</td>
<td>National Institute of Occupational Safety and Health</td>
</tr>
<tr>
<td>NOF</td>
<td>Number of Failures</td>
</tr>
<tr>
<td>POF</td>
<td>Probability of Failure</td>
</tr>
<tr>
<td>RFRI</td>
<td>Roof Fall Risk Index</td>
</tr>
<tr>
<td>RMR</td>
<td>Rock Mass Rating</td>
</tr>
<tr>
<td>RQD</td>
<td>Rock Quality Designation</td>
</tr>
<tr>
<td>SRF</td>
<td>Stress Reduction Factor</td>
</tr>
<tr>
<td>UCS</td>
<td>Uniaxial Compressive Strength</td>
</tr>
<tr>
<td>WRAC</td>
<td>Workplace Risk Assessment and Control</td>
</tr>
</tbody>
</table>
List of Publications

This doctoral dissertation consists of a summary and of the following publications, which are referred to, in the text by their numerals


Author’s Contribution

**Publication 1:** The author wrote the entirety of the text, classified underground mining methods under sub categories for suitability of risk assessment, created the alpha-numeric ranking system for mining operation based on the classification, described geotechnical hazard potential (GHP) for different mining classification and drew the conclusion. Rinne commented on the manuscript.

**Publication 2:** The author wrote the entirety of the text, developed the numerical ranking system to plan the risk assignment process and select risk assessment tools, classified risk assessment approaches, prepared the scope document with the subdivision of risk assessment requirements and drew the conclusion. Rinne commented on the manuscript.

**Publication 3:** The author wrote the majority of the text, wrote large parts of chapter 2 covering steps involved in Geotechnical Risk Assessment (GRA) and selection of the right risk assessment method, designed and described the fault tree analysis (FTA) diagram for strainburst in underground mines, designed and described the Event Tree Analysis (ETA) following a strainburst, wrote entirety of chapter 3 describing the financial quantification of risk using an FN diagram. Uotinen wrote the sections concerning the preceding research on DynaMine, contributed towards the Event Tree Analysis, and wrote the discussion and conclusions chapters. Janiszewski wrote the Geotechnical Hazard Potential and Geotechnical Risk Assessment descriptions, Szydlowska wrote parts of the introduction and Geotechnical Risk Management, Siren wrote a part of the introduction, GRM and discussion. Rinne commented on the manuscript.

**Publication 4:** The author wrote majority of the text, summarised the results of the interview from the metal mine, defined the current risk methodology being used in the mine, developed and wrote the alternative risk assessment method using Bayesian network and calibration of the alternative risk assessment using instrumentation data. The author also wrote part of the discussion section. Kiuru described the interview process and Janiszewski wrote sections describing the general principle of geotechnical risk assessment. Uotinen wrote part of the discussion and conclusion section. Rinne commented on the manuscript.
Publication 5: The author coordinated the writing of the article, wrote majority of the text, described the Bayesian network approach for forward and backward inferencing, carried out parameter learning on data collected from US coal mines over 19 years, carried out distribution fitting using Bayesian network for roof fall frequencies, created the spalling risk model, combined multiple probability distributions using parameter learning to forecast incidents, explained the use of Bayesian network in real time risk assessment and drew the conclusions. Uotinen contributed to the calculation examples and wrote the conclusions chapter. Rinne commented on the manuscript.
1. Introduction

The mining industry is an inherently uncertain business, given the amount of variability and uncertainty arising from commodity prices and the operational risks arising from accidents and incidents. With the depletion of resources over time, the depth of mining is constantly increasing, posing serious risks of geotechnical incidents. Underground mining activities suffer from a risk of accidents arising from geotechnical uncertainties resulting from the difficulty of data acquisition and the need for localised instrumentation to warn against an impending failure. The capital-intensive nature of mining requires these uncertainties to be addressed in the best possible way.

A geotechnical accident in a mine is a high-consequence event and can cause severe damage to routine operations to such an extent that mining has to be suspended for extended periods for rescue and rehabilitation. The consequences of geotechnical accidents can include loss of property, grievous bodily harm, permanent loss of ore, damage to the environment, loss of reputation, etc. (Blumenstein et al., 2011). Despite the development of advanced geotechnical modelling and design tools over the years, geotechnical incidents in underground mines are not uncommon. The severity of the consequences, coupled with uncertain conditions in underground mining, requires these risks to be assessed in advance during various stages of mining so that appropriate monitoring and mitigation measures can be put in place.

Risk assessment for general workplace health and safety is an extensively researched subject and a lot of work has been done in this field to come up with best working practices and procedures to ensure a safe working environment (Pinto et al., 2011). The level of uncertainty in such accidents and the parameters that affect it are generally visible. Geotechnical accidents, on the other hand, can be caused by factors which may be difficult to assess through visual inspections and require additional instrumentation and data collection (Baecher and Christian, 2003). Mining in an area with no prior mining history would mean that geotechnical data needs to be collected through expensive geophysical or geological methods. Even when the prior mining history and geological data are available, operational and human error can contribute to the creation of adverse geotechnical conditions leading to accidents. Geotechnical risk assessment (GRA) in underground mines therefore requires a formal framework to plan and carry out detailed evaluation through all the stages of mining. GRA follows the same principle as a normal risk assessment and can be defined as shown in Equation (1) (Fenton and Griffiths, 2008).
where GL is the likelihood of a geotechnical hazard being present and GS is the severity of the accident caused by the hazard. Figure 1 shows the risk assessment framework to be used when carrying out risk assessment (Mishra et al., 2017).

\[
\text{Geotechnical Risk} = \text{GL} \times \text{GS}
\]

This thesis covers the various steps involved in carrying out an extensive geotechnical risk assessment, ranging from the collection and use of data from the early stages of mining for risk classification (Publication 2) to carrying out a detailed risk assessment using quantitative and subjective data by the use of Bayesian networks (Publications 4 and 5). The process of risk assessments has been sub-divided into its elementary steps and guidelines have been provided to choose the most appropriate risk assessment method (Publication 1). Root cause and failure analysis for geotechnical incidents have been covered in the form of a Fault Tree – Event Tree Analysis (FTA – ETA) (Iverson et al., 2001, Andrews and Dunnett, 2000) and a modified F-N diagram approach has been presented to quantify and represent risk (Publication 3).

1.1 Research problem

The geotechnical information available for risk assessment varies depending on the stage of mining. Pre-feasibility studies often rely on information collected through core drilling and they largely focus on the operational feasibility from the point of view of an appropriate mining method. Data collected
through core drilling isn’t enough to make accurate reinforcement cost assessments. As mining progresses to bankable feasibility and the operational stage, additional data is collected through drilling, instrumentation, and observations. In order to create a culture of risk awareness and to justify investment in risk mitigation measures, it is important to incorporate risk assessment into stages as early as pre-feasibility and then expand it as additional information becomes available. Publication 2 proposes a geotechnical risk classification method to cover different underground mining methods with varying amounts of geotechnical information. The classification uses bulk rock mass properties which are collected as part of routine mining operations and ranks them on the basis of their risk of geotechnical failures. An alphanumeric ranking system in the form of the Geotechnical Hazard Potential (GHP) has been proposed to include geotechnical risk assessment from the early stages of mine planning and a feasibility study.

It is important to define the appropriate scope of the risk assessment in advance so that the process is completed in the fastest possible time and in an efficient manner. Publication 1 provides detailed guidelines on preparing the detailed scope of a geotechnical risk assessment. Given the extent of the research conducted on general health and safety, there are numerous risk assessment tools available for use (Pinto et al., 2011). As mining operations progress and additional data becomes available, it becomes important to choose the appropriate risk assessment tool, the one which best utilises the geotechnical information and resources available. Risk assessment methods, which are popular in the mining industry, are a misnomer as they help in identifying which possible hazards can result in an accident. However, they do not dwell further on what the probability of hazards occurring is or on their consequences. Publication 1 tries to bridge this knowledge gap by reclassifying the existing tools into ‘Risk Identification Tools’ to avoid confusion and to ensure that the probability calculation gets the attention it needs. Publication 1 further classifies the hazard and consequence assessment techniques into risk assessment parameters and risk assessment approaches and provides a numerical ranking method to select the appropriate risk assessment parameter and risk assessment approach.

After a potential geotechnical incident such as a roof collapse or a strainburst is selected for risk assessment, the incident needs to be evaluated in terms of the different ways in which it can manifest itself in the mine. These individual contributors to the incident need to be broken down further so that the mine can arrive at the root cause or causes. The extent of the damage caused by a geotechnical incident depends not only on the severity of the incident itself but also the prevailing conditions in which it happens, which affect the severity of the consequences. Publication 3 proposes the use of Fault Tree Analysis (FTA) (Iverson et al., 2001) to break down an incident into its underlying causes by using a strainburst as an example. Publication 3 also demonstrates the use of Event Tree Analysis (ETA) (Andrews and Dunnett, 2000) to model the severity of the incident and then goes on to show the numerical ranking of the measured risk using a modified F-N diagram (Pine, 2011).
For new mines with no prior mining and/or geotechnical incident history in the region, carrying out a quantitative geotechnical risk assessment can be difficult. While a qualitative risk assessment can help in the absence of data, it can be very broad in nature and can suffer from bias and other human errors. Existing mines with an available incident history can also suffer from this problem as a detailed root cause investigation into each incident may not have been carried out in the past. Publications 4 and 5 attempt to solve this problem with the use of Bayesian Networks (BN). In this thesis, the use of parameter learning on historical incident frequency to forecast future incidents is presented. Parameter learning using BN has also been used to determine the appropriate probability distributions that best fit the incident data.

The overall objective of this research is to formulate a set of guidelines for geotechnical risk assessment for underground mines to work with both qualitative and quantitative data and the ability to carry it out in real time and to establish a risk representation tool suited to the mining industry. In summary, the research questions explicitly addressed in this thesis are:

1. How to classify mines on the basis of their geotechnical risk potential from the early stages of mine planning?
2. How to define the scope of a formal geotechnical risk assessment (GRA)?
3. How to choose the appropriate risk assessment tools according to the scope of the GRA?
4. How to carry out a quantitative GRA when historical geotechnical incident frequencies are available?
5. How to carry out a quantitative GRA by combining multiple probability distributions to improve incident forecasting?
6. How to carry out a GRA in real time and how to represent the measured risk for easy communication?

1.2 Objectives

The following objectives were set to address the research problems that had been identified:

1. Formulate a geotechnical risk classification system to work with limited data in the early stages of the mine with the potential to be extended to later stages.
2. Establish guidelines to define the scope of a formal geotechnical risk assessment.
3. Formulate a selection tool to choose between the available geotechnical risk assessment (GRA) tools that best suit the scope of the GRA.
4. Formulate a risk assessment tool to work with expert opinions in the absence of historical data.
5. Establish a method to learn from historical incident frequencies to create future incident forecasts.
6. Formulate a real-time geotechnical risk assessment, risk representation, and risk mitigation guideline.
1.3 Scope

In this thesis, the authors evaluated the various available risk assessment tools in terms of their suitability for geotechnical incidents. The study was limited to underground mines. While various qualitative risk assessment methods are discussed in brief, quantitative risk assessment is limited to frequentist and Bayesian methods. The frequentist method for risk assessment is limited to Fault Tree and Event Tree Analysis by using a strainburst as an example of geotechnical failure. The Bayesian method for risk assessment is demonstrated by the use of Bayesian networks and is limited to roof falls in coal mines as an example.

1.4 State of the art of geotechnical risk assessment

A state-of-the-art review was carried out for risk assessment practices across industries by subdividing the process into risk identification, risk quantification, and risk communication. Each sub-process was reviewed through a literature review and mine site visits. The results of the review are summarised here. Most of the risk assessment process across the industry combines the risk identification and quantification processes (Mishra, 2012). It is recommended that the geotechnical risk assessment process is divided into 2 steps. First step deals with breaking down the hazards into the various ways they can be manifested while the second step deals with risk quantification.

Hazard identification tools have been used in different formats across multiple industries. Workplace risk assessment and control (WRAC) has a wide application in several industries and utilises a risk assessment team to evaluate the potential cause of failure in a system (Joy, 2004). WRAC is used for quick risk assessment in the mining and construction industries for routine identifications of hazards prior to commencing a job. Each potential event is then defined using its likelihood and consequences to measure the risk. Failure mode and effects analysis (FMEA) involves the identification of the failure modes of one single element, along with their effect, and helps identify various ways in which the system can fail (Robertson and Shaw, 2003). FMEA is popular in reliability engineering to identify failure modes and is used in industries such as aviation, oil and gas, space engineering, etc. Bow Tie Analysis (BTA) is used for the risk assessment of major hazards that can lead to severe consequences in terms of multiple fatalities and catastrophic financial loss (Iannacchione et al., 2007c). BTA breaks the assessment down into both pre-accident and post-accident control measures, thus evaluating the robustness of the emergency response in place in an organisation. Fault Tree Analysis (FTA) evaluates the root cause behind an incident by breaking it down into its intermediate and root causes. FTA also has provisions for easy-to-use probabilistic expressions to represent the likelihood of an incident. FTA has been used in the past to carry out geotechnical hazard identification in underground mines (Iverson et al., 2001). Event Tree Analysis (ETA) is used to describe the various consequences that may happen following an incident. ETA has been used to assess
the consequences following rock slides on Norwegian rock slopes (Lacasse et al., 2008). The ‘Five why’ method is prominent in manufacturing industry to identify the series of causes behind an incident. ‘Five why’ follows the principle of iterative interrogation to determine the primary cause of an incident. The Five why technique has been used in the underground mining industry in the past to investigate incidents (Öztürk et al., 2018). The Ishikawa diagram or fishbone diagram is another method for breaking down an incident into its preliminary causes by dividing them into sub-categories such as material, personnel, environment, machine, etc. The use of Ishikawa diagrams has been demonstrated in the past to assess and reduce geotechnical risks (Gierczak, 2014).

Extensive work has been done in the past to quantify the risk once the hazard has been identified using qualitative and quantitative parameters (Brown, 2012, Choi et al., 2004, Einstein, 1996, Mishra, 2012, Pinto et al., 2011, Honjo et al., 2009). The probabilistic quantification of risk uses simulations such as Monte Carlo to quantify risk and has been used to quantify geotechnical risks (Dershowitz and Einstein, 1984, Galvin et al., 1999, Baecher and Christian, 2003, Mishra et al., 2017). Historical incident data without causation can also be used to create the probability distribution of incident frequencies to forecast future failures (Duzgun and Einstein, 2004). Another form of risk quantification is with the use of empirical methods such as the Q-system (Barton, 1987), the roof fall risk index method (Iannacchione et al., 2007a), or Mathews’ stope stability graph method (Mathews et al., 1981), etc., and uses results calibrated with data collected across several mines to evaluate the potential for failure. Bayesian networks are another way of quantifying risks by combining the conditional probability relationships between the causal factors leading to an incident. It has been used in the past to carry out dam risk assessment (Smith, 2006), tunnel risk assessment (Sousa and Einstein, 2007, Spackova and Straub, 2011), construction projects (Zhang et al., 2014), failure assessment in process plants (Meel and Seider, 2006), etc. Bayesian networks have also been used in the mining industry to assess rock fall hazards (Sousa and Einstein, 2012).

Risk representation following risk quantification has been carried out in different ways in the past. A 5 X 5 risk matrix is a commonly used format in the mining and construction industries for qualitative risk assessment. A risk matrix is drawn by ranking likelihood and consequences on a scale of 1 to 5 and plotting the assessed risk on the basis of the score for likelihood and consequences. A quantitative risk is easier to represent through actual risk frequency values, such as the potential loss of x million euros per year or a stoppage of x operational hours per month, etc. A quantitative risk can also be represented using a modified FN diagram which shows the likelihood of an incident and the potential financial loss using a logarithmic graph (Pine, 2011). A typical FN diagram as shown in Figure 17 also assists in plotting tolerable and intolerable risks on the same graph for better communication.
2. Research Method

The research was carried out by means of a literature review, visits to mine sites, and consultations with risk management professionals and mine site representatives. One of the problems with geotechnical risk management identified through the literature review and site visits was the lack of a risk management framework that was practical for on-site use by employees. Geotechnical risk management was considered to be an ancillary job instead of being part of the mine planning process from the pre-feasibility stage. A preliminary risk classification system for underground mines was developed by reviewing and combining existing methods for measuring rock competency and the stability of underground operations. Existing risk management tools were reviewed for their suitability for geotechnical risk assessment. Appropriate hazard identification tools were identified and proposed on the basis of the amount of data available. The process of defining the scope of a risk assessment was defined through the literature review and consultation with mines. A modified FN diagram was developed to represent the risk and to enable the tracking of mitigation measure performance. The suitability of Bayesian networks for carrying out failure forecasting was demonstrated by evaluating 1,148 roof collapse incidents across 12 mines over 19 years.

A new geotechnical risk classification system which incorporates both the level of geotechnical information and type of mining was proposed (Publication 2). A new selection tool was proposed for choosing between probabilistic, deterministic, and empirical risk assessment methods, which could be performed in parallel to the process of defining the scope of risk assessment (Publication 1). A new method of representing the risk by combining Fault Tree and Event Tree results was produced (Publication 3). The use of a Bayesian network to perform an expert opinion-based risk assessment was demonstrated (Publication 4). A risk assessment tool was proposed that learned from historical accident frequencies using parameter learning to forecast future incidents. A new method to combine multiple probability distributions to forecast risk was proposed (Publication 5).

In conclusion, the state of the art was further developed by using the results from all the publications. Publications 1 and 2 discuss the process of preparing for a risk assessment. Publications 3 and 4 discuss various tools with which the risk can be calculated in both the presence and absence of historical data. Publication 5 proposes a new tool to represent and monitor risk in an organisation.
3. Preliminary risk classification for underground mines

The first step in the proposed geotechnical risk management framework is to carry out a preliminary risk classification in underground mines. The preliminary classification can then be used to justify future investments in risk assessment and risk mitigation. With the improvement of data collection technologies, geotechnical data acquired from the early stages of mine prospecting can be utilised to create a risk classification system. This chapter discusses the categorisation of mining sections on the basis of their geotechnical risk potential and the use of an alphanumeric naming system to represent the risk (Publication 1). The proposed risk classification is based on the stage of mining and mining properties. The mining stages are divided into pre-feasibility, bankable feasibility, and mining operations stages. Mining properties are further subdivided into two classes, namely the mining method and rock mass characteristics. The sub-classifications and their impact on the geotechnical risk are explained further below.

3.1 Sub-classification based on mining properties

3.1.1 Mining Method

Mining methods have been classified in the past as artificial, natural, and caving methods (Brady and Brown, 2013), hard rock vs. soft rock, and conventional mining vs. novel practices (Hamrin et al., 2001). For the purpose of risk classification, mining methods have been subdivided into four categories, as stated below. Although each of the mining methods discussed has certain generic risks associated with it (Hebblewhite, 2003), it has not been compared against each other for suitability in this sub-classification. This is owing to the fact that the selection of mining methods is not only dependent on geotechnical parameters but is dictated by geological and economic constraints as well. Each mining method has been assigned an alphabetical code in parentheses to be used later in the risk classification (Publication 1).
Open stoping methods (O)
All mining methods which use natural support in the form of pillars and/or artificial support in the form of rock reinforcements such as roof bolts, wire mesh, shotcrete, etc. have been classified under open stoping methods. Sublevel stoping with and without backfill, vein mining, cut-and-fill mining, shrinkage stoping, vertical crater retreat, and bighole stoping are examples of mining methods which fall under this category. These methods are represented by the letter “O” for the purpose of classification. The mining methods in this group are characterised by low country rock displacement and high stored strain energy in the rock. The degree of the rock stress distribution provided by the support depends on the thickness of the pillar, rock competence of the pillar, quality of the reinforcement used, quality of installation, etc. and this in turn determines the level of geotechnical risk arising from the mining method.

Caving methods (C)
All mining methods where the excavated rock mass is allowed to cave/collapse are classified under this category. The mining methods in this category are characterised by high country rock displacement and low stored strain energy. While relieving stored stress helps reduce the risk of geotechnical incidents, the uncertainty in the timing and extent of caving adds to the geotechnical risk, along with the post-caving risks of air-blast and subsidence. Examples of mining methods grouped in this category are sublevel caving, block caving, panel caving, etc. The mining methods in this group are represented by the letter “C”.

Longwall mining methods (L)
Longwall mining methods are transitional methods involving face support prior to caving. Although popular in coal seam mining, they are used in metaliferous mines as well. Given the combined nature of support and caving, the geotechnical risks in these methods can be common to both the methods. The mining methods in this group are represented by the letter “L”.

Room and pillar mining methods (R)
The mining methods in this group involve leaving pillars to support the mining faces. However, these pillars are subsequently mined to extract resources by means of artificial support and caving is subsequently used for long-term stress release. Similar to longwall mining, this method has found its use outside coal in massive tabular ore bodies. Given their nature, the geotechnical risks of these methods are common to the “O” and “C” mining groups. The mining methods in this group are represented by the letter “R”.

21
3.1.2 Rock mass characteristics

The risk classification system using rock mass properties is derived from the existing rock mass classification systems with little or no modification. The purpose behind this is to keep the data collection process simple and integrate existing practices. The amount and quality of data collection, however, varies for different stages of mining (Publication 1). In order to cater for the increase in information, the rock mass property-based classification is divided into three stages of mining, namely “Pre-feasibility”, “Bankable feasibility”, and “Mining operations”.

**Pre-feasibility stage (1)**
The pre-feasibility stage of mining is represented by the Arabic numeral “1”. Geotechnical information at this stage is limited to the information available from exploratory drilling and mapping of outcrops or existing tunnels. Barton’s Q-system (Barton et al., 1974) is therefore proposed to be used for classifying rock mass competence as shown in Equation (2):

\[
Q = \frac{RQD}{J_n} \times \frac{J_r}{J_a} \times \frac{J_w}{SRF}
\]  

where RQD is the Rock Quality Designation index (Deere, 1988), J_n is the joint set number, J_r is the joint roughness number, J_a is the joint alteration number, J_w is the joint water reduction factor (fixed as 1 for risk-based classification), and SRF is the stress reduction factor. The risk classification based on Q is further subdivided into five levels and each level is represented by the Roman numerals “I” to “V”. The proposed sub-classification is subjective and not validated on field data. In the later chapters it is discussed, how a subjective opinion-based risk assessment can be calibrated using a Bayesian network and backward inferencing (Publications 4 and 5). The sub-classification is shown in Table 1.

<table>
<thead>
<tr>
<th>Range of Q value</th>
<th>Classification code</th>
<th>Rock competency</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.001 - 1</td>
<td>I</td>
<td>Very poor</td>
</tr>
<tr>
<td>1 - 4</td>
<td>III</td>
<td>Poor</td>
</tr>
<tr>
<td>4 - 10</td>
<td>IIII</td>
<td>Fair</td>
</tr>
<tr>
<td>10 - 40</td>
<td>IV</td>
<td>Good</td>
</tr>
<tr>
<td>40 - 1000</td>
<td>V</td>
<td>Very good</td>
</tr>
</tbody>
</table>

**Bankable feasibility stage (2)**
The bankable feasibility stage is represented by the Arabic numeral “2”. Geotechnical information at this stage is still limited, with the exception of additional core drills. At this stage, the classification still applies to the entire mine or a large section of the mine where additional geotechnical information has
been collected. The proposed rock mechanical parameter for the classification is the use of ‘Safety Margin’ as shown in Equation (3):

\[
Safety\ Margin\ (SM) = \frac{in-situ\ rock\ strength}{major\ principle\ stress} - 1
\]  

(3)

The assumption at the bankable feasibility stage is that sufficient data is available to carry out a Q-classification. If not, the classification must use only Q-system results as per the pre-feasibility stage guidelines. When both safety margin and Q-system results are available, the worse of the two values is used for the risk classification. Safety Margin results have subsequently been divided into five subcategories, represented by the Roman Numerals “I” to “V” as shown in Table 2.

<table>
<thead>
<tr>
<th>Range of SM</th>
<th>SM-based quality of rock</th>
<th>Q-based rock competency</th>
<th>Classification code</th>
<th>Rock competency (worse of SM and Q)</th>
</tr>
</thead>
<tbody>
<tr>
<td>-1 to -0.8</td>
<td>Very low</td>
<td>Very low</td>
<td>2I</td>
<td>Very low</td>
</tr>
<tr>
<td>-0.8 to 0</td>
<td>Low</td>
<td>Low</td>
<td>2II</td>
<td>Low</td>
</tr>
<tr>
<td>0 to 0.5</td>
<td>Fair</td>
<td>Fair</td>
<td>2III</td>
<td>Fair</td>
</tr>
<tr>
<td>0.5 to 2</td>
<td>High</td>
<td>High</td>
<td>2IV</td>
<td>High</td>
</tr>
<tr>
<td>2 and above</td>
<td>Very high</td>
<td>Very High</td>
<td>2V</td>
<td>Very high</td>
</tr>
</tbody>
</table>

**Mining operations stage (3)**

As mining operations begin, additional geotechnical information is collected as part of a planned data collection regime or though the geotechnical mapping of exposed rock surfaces. The mining operations stage also provides information through incident investigations carried out for any geotechnical incident in the mine. Classification at this stage can cover either the entire mine or various sections of the mine. The Stability Number (N) as proposed by Mathews et al. (1981) for stope stability analysis has been modified to be used as the classification method for the mining operations stage. Similar to the bankable feasibility stage, the Stability Number is used as an additional classification system beyond the safety margin and Q-system results. When both bankable feasibility and mining operations classification results are available, the worse of the two is used for the classification. The modified stability number \( N_r \) is given by:

\[
N_r = Q \times B \times C
\]  

(3)

where Q is the Barton’s Q-number with Jw fixed as 1. Factor B, which deals with the influence of discontinuity on rock stability, is calculated using the chart proposed under Mathews’ stability graph method as shown in Figure 2.
Figure 2. B parameter calculation for modified stability number (Mathews et al., 1981)

Factor C can be calculated as proposed in the stability number N calculation as:

\[ C = 8 - 7 \cos \alpha \]  

(4)

where \( \alpha \) is the dip of the excavation from the surface of excavation. Of the C values from all surfaces, the lowest must be taken. Similar to the previous two classifications, the results are divided into five sub-categories and denoted by the Roman numerals “I” to “V”. The results from the rock mass classification system at the mining operations stage are shown in Table 3.

Table 3. Rock mass classification for risk for mining operations stage.

<table>
<thead>
<tr>
<th>Range of ( N_r )</th>
<th>N-based quality of rock</th>
<th>SM-based quality of rock</th>
<th>Classification code</th>
<th>Rock competency (worse of SM and ( N_r ))</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0001 – 0.6</td>
<td>Very low</td>
<td>Very low</td>
<td>3I</td>
<td>Very low</td>
</tr>
<tr>
<td>0.6 - 7</td>
<td>Low</td>
<td>Low</td>
<td>3II</td>
<td>Low</td>
</tr>
<tr>
<td>7 - 30</td>
<td>Fair</td>
<td>Fair</td>
<td>3III</td>
<td>Fair</td>
</tr>
<tr>
<td>30 - 250</td>
<td>High</td>
<td>High</td>
<td>3IV</td>
<td>High</td>
</tr>
<tr>
<td>250 and above</td>
<td>Very high</td>
<td>Very high</td>
<td>3V</td>
<td>Very high</td>
</tr>
</tbody>
</table>
3.2 Summary of classification

The results from the mining method and rock mass classification can be combined to create an alphanumeric risk identification system for mines (Publication 1). All the possible combinations of the classification are shown in Tables 4, 5, and 6.

**Table 4.** Pre-feasibility stage risk-based classification

<table>
<thead>
<tr>
<th>Mining Method</th>
<th>Rock competency – high to low</th>
</tr>
</thead>
<tbody>
<tr>
<td>Open stoping</td>
<td>O1I O1II O1III O1IV O1V</td>
</tr>
<tr>
<td>Caving</td>
<td>C1I C1II C1III C1IV C1V</td>
</tr>
<tr>
<td>Longwall</td>
<td>L1I L1II L1III L1IV L1V</td>
</tr>
<tr>
<td>Room &amp; pillar</td>
<td>R1I R1II R1III R1IV R1V</td>
</tr>
</tbody>
</table>

**Table 5.** Bankable feasibility stage risk-based classification

<table>
<thead>
<tr>
<th>Mining Method</th>
<th>Rock competency – high to low</th>
</tr>
</thead>
<tbody>
<tr>
<td>Open stoping</td>
<td>O2I O2II O2III O2IV O2V</td>
</tr>
<tr>
<td>Caving</td>
<td>C2I C2II C2III C2IV C2V</td>
</tr>
<tr>
<td>Longwall</td>
<td>L2I L2II L2III L2IV L2V</td>
</tr>
<tr>
<td>Room &amp; pillar</td>
<td>R2I R2II R2III R2IV R2V</td>
</tr>
</tbody>
</table>

**Table 6.** Mining operations stage risk-based classification

<table>
<thead>
<tr>
<th>Mining Method</th>
<th>Rock competency – high to low</th>
</tr>
</thead>
<tbody>
<tr>
<td>Open stoping</td>
<td>O3I O3II O3III O3IV O3V</td>
</tr>
<tr>
<td>Caving</td>
<td>C3I C3II C3III C3IV C3V</td>
</tr>
<tr>
<td>Longwall</td>
<td>L3I L3II L3III L3IV L3V</td>
</tr>
<tr>
<td>Room &amp; pillar</td>
<td>R3I R3II R3III R3IV R3V</td>
</tr>
</tbody>
</table>

These classification codes can now be used to rank and communicate preliminary risk levels in underground mines. For instance, a section labelled C3II would indicate a caving method (C) evaluated during the mining operations stage (3) and being classified as having a rock competency of II on a scale from I to V in descending order of rock competency.

3.2.1 Geotechnical Hazard Potential (GHP)

The risk classification system is meant to signify the relative risk in a mine. The simplicity of the system is intended for preliminary risk assessment so that risk management becomes part of the mining process from the early stages (Hanson et al., 2005). In line with this principle, a mine or a section of the mine can be evaluated on the basis of its potential to pose a geotechnical hazard. Table 7 summarises the Geotechnical Hazard Potential (GHP) of a mine.
on the basis of the result of the risk-based classification system (Publication 1). Similar to the sub-classification based on mining properties, the Geotechnical Hazard Potential (GHP) shown in Table 7 is subjective and can be calibrated using field data using Bayesian networks.

Table 7. Geotechnical Hazard Potential (GHP) on basis of risk-based classification (Publication1)

<table>
<thead>
<tr>
<th>GHP</th>
<th>Description</th>
<th>Mining Category</th>
</tr>
</thead>
</table>
| Very Low (1) | • Negligible chances of hazards arising from bulk rock mass properties.  
• Hazards can largely arise from random natural events, unforeseen discontinuity, human error, etc. | O1V, C1V (for footwall), C1II (for hanging wall), L1V (for footwall), L1II (for hanging wall), R1V  
O2V, C2V (for footwall), C2II (for hanging wall), L2V (for footwall), L2II (for hanging wall), R1V  
O3V, C3V (for footwall), C3II (for hanging wall), L3V (for footwall), L3II (for hanging wall), R1V |
| Low (2)  | • Minor chances of hazards arising from bulk rock mass properties. This can be in terms of minor ravelling and spalling.  
• Hazards arising from random natural events, unforeseen discontinuity, and human error. The extent of the damage resulting from such random events is noticeable but does not hamper routine mining activity. | O1V, C1V (for footwall), C1I (for hanging wall), L1V (for footwall), L1I (for hanging wall), R1IV  
O2V, C2V (for footwall), C2I (for hanging wall), L2V (for footwall), L2I (for hanging wall), R2IV  
O3V, C3V (for footwall), C3I (for hanging wall), L3V (for footwall), L3I (for hanging wall), R3IV |
| Fair (3) | • Fair chances of hazards arising from bulk rock mass properties. This can be routine if the rock mass is not supported/reinforced.  
• Hazards arising from random natural events, unforeseen discontinuity, and human error. The extent of the damage from this can be higher than the routine visible failures. This can cause substantial damage to production. Loss of productivity is recoverable over a short span (couple of weeks) | O1III, C1III (for footwall), C1II (for hanging wall), L1III (for footwall), L1II (for hanging wall), R1III  
O2II, C2II (for footwall), C2I (for hanging wall), L2II (for footwall), L2I (for hanging wall), R2II  
O3I, C3I (for footwall), C3II (for hanging wall), L3I (for footwall), L3II (for hanging wall), R3II |
| High (4) | • High frequency of hazards arising from bulk rock mass properties. Accidents cause productivity losses recovered over weeks.  
• An unsupported site may not be safe for on-site risk assessment itself.  
• Hazards arising from random natural events, unforeseen discontinuities, and human error. Such hazards cause major damage to production. May lead to clo | O1I, C1I (for footwall), C1II (for hanging wall) L1I (for footwall), L1IV (for hanging wall), R1II  
O2II, C2II (for footwall), C2IV (for hanging wall) L2II (for footwall), L2IV (for hanging wall), R2II |
<table>
<thead>
<tr>
<th>GHP</th>
<th>Description</th>
<th>Mining Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very</td>
<td></td>
<td>(5)</td>
</tr>
<tr>
<td>High</td>
<td>• Very high frequency of hazards arising from bulk rock mass properties. Accidents cause losses of productivity which may not be recovered over the year.</td>
<td>O3II, C3II (for footwall), C3IV (for hanging wall), L3II (for footwall), L3IV (for hanging wall), R1II</td>
</tr>
<tr>
<td></td>
<td>• Site for risk assessment must not be visited without reinforcement and a couple of days of observation.</td>
<td>O1I, C1I (for footwall), C1V (for hanging wall), L1I (for footwall), L1V (for hanging wall), R1I</td>
</tr>
<tr>
<td></td>
<td>• Hazards arising from random natural events, unforeseen discontinuities, and human error. Such hazards may cause permanent loss of raw material in the form of trapped ore. Severe financial losses and overall net present value (NPV) of project may be affected.</td>
<td>O2I, C2I (for footwall), C2V (for hanging wall), L2I (for footwall), L2V (for hanging wall), R2I</td>
</tr>
<tr>
<td></td>
<td></td>
<td>O3I, C3I (for footwall), C3V (for hanging wall), L3I (for footwall), L3V (for hanging wall), R3I</td>
</tr>
</tbody>
</table>

While the mining category included in the GHP is meant as a guideline, any additional geotechnical observation which indicates a substantial geotechnical risk, such as evidence from adjacent mines, incidents during the development of the mine, the criticality of the mining section, etc. can be included in assigning the GHP value. This exercise can then be used to justify resources for additional investigation and formal risk assessment if needed as demonstrated by Janiszewski (2014).
4. Preparing scope of detailed geotechnical risk assessment (GRA)

A detailed risk assessment helps in identifying potential failure in advance and allocating finances for measures and expenses that may be needed to mitigate the identified risks. A risk assessment in turn helps build faith in a safe working environment among the employees and a sustainable business among the stakeholders. However, a detailed risk assessment can also overrun its time and budget, become non-specific or too broad, and not be fit for purpose. It is therefore important to design the scope of a geotechnical risk assessment (GRA) carefully before its execution. This chapter focusses on the element of geotechnical risk assessment and proposes a selection criterion for choosing an appropriate risk assessment tool (Publication 2).

4.1 Elements of a Geotechnical Risk Assessment (GRA)

In order to simplify the scope evaluation process, the GRA requirement has been subdivided into five broad categories as listed below:

1. **GRA type**: GRA type considers the primary reason why the risk assessment is being carried out. This has been further subdivided into three categories. The first category is **proactive GRA**, which is performed in advance of a planned operation. The main aim of this GRA is to prevent the first incident on-site. For instance, carrying out a risk assessment of a rock burst in a new mine with no recorded rock burst incidents falls under proactive GRA. The second category is called **reactive GRA**. Reactive GRA itself can be of two types. When reactive GRA is carried out in response to an incident or signs of imminent failure, it is called **symptom-based reactive GRA**. Risk assessment carried out to monitor the performance of control measures that have been implemented, such as roof bolt installation, controlled blasting to release stress, or backfilling to reduce risk, is called **routine reactive GRA**. The third category of GRA type is **change implementation GRA**, in which the risk assessment is carried out to evaluate the impact of changing a mining process which influences the geological risk. A change of support type, mining method, mining sequence, etc. fall under this GRA type.
2. **GRA area scale:** This subcategory covers the area covered by the risk assessment and has been further subdivided into small- and large-scale GRA. Small-scale GRA covers individual sections of a mine such as stopes, individual pillars, faces, etc. This risk assessment is often informal and performed on a daily basis as part of a normal pre-work inspection. The results of these inspections, however, may warrant the need for a detailed and formal risk assessment. Large-scale GRA covers the entire mine or large sections of the mine, including multiple stopes or a network of drifts. The results of this GRA play a role in mine layout and sequencing design and cover broader risks such as the risk of seismicity, impact of an air blast, large-scale collapse, etc.

3. **Hazard scope:** It defines the number of hazards being looked at in the GRA. This is further divided into hazard-specific GRA, where a section or multiple sections of the mine are evaluated for one specific hazard, and site-specific GRA, where a section or multiple sections are evaluated for all the possible geotechnical hazards in that section/those sections.

4. **Reporting requirement:** The audience of the proposed risk assessment defines the reporting requirement. If the risk assessment is carried out to be used within the organisation, it is sub-classified as internal reporting GRA. However, if the GRA is carried out to comply with some legal/regulatory obligations, in response to an incident or hazard as mandated by law or some other regulatory body, for stakeholders outside the company etc., it is grouped under external reporting GRA.

5. **Resources available:** This classification covers the resources in terms of the time, money, manpower, and information available to carry out the risk assessment and has been subdivided into high, average, and low resource availability. High resource availability indicates the presence of sufficient personnel, instrumentation, and geotechnical information to assess the likelihood and consequences of the hazard. Average resource availability indicates a lack of or insufficient current geotechnical information but sufficient personnel to carry out the risk assessment. When the geotechnical information and manpower available for the risk assessment are both low, the GRA is classified under low resource availability.

### 4.2 Hazard Identification Tools

The first step in carrying out the risk assessment is to evaluate the potential hazard for its underlying root causes. The following four tools have been recommended to carry out hazard identification when carrying out the risk assessment (Mishra, 2012, Mishra and Rinne, 2014).

1. **Workplace risk assessment and control (WRAC):** WRAC (Joy, 2004) is an informal way of carrying out a quick assessment of the workplace for hazards. This can be carried out with little training of the mine personnel and a large part of the mine can be covered as part of the day-to-
Preparing scope of detailed geotechnical risk assessment (GRA)

day operations. Hazards identified from each part can then be recorded and analysed to evaluate their prevalence and priority. Given its ease of use and ability to conduct a general risk assessment, WRAC is suitable for use for small-scale and site-specific risk identification.

2. **Failure Mode and Effect Analysis (FMEA):** FMEA (Robertson and Shaw, 2003) involves breaking down a process into its individual elements and evaluating them individually for their impact. This method is popular in carrying out the risk assessment of equipment to evaluate its overall reliability. This system can be replicated in mines by dividing the mine into haul roads, stopes, drifts, etc. and individually assessing the impact of each on the overall mine risk. Table 8 shows a standard template to carry out FMEA. FMEA can be used to determine the safety of large systems for various modes of failures. This makes them suitable for large-scale and site-specific risk identification.

<table>
<thead>
<tr>
<th>Mine Element</th>
<th>Failure Mode</th>
<th>Failure Effect</th>
<th>Likelihood</th>
<th>Consequence</th>
<th>Risk Ranking</th>
</tr>
</thead>
<tbody>
<tr>
<td>Section 1</td>
<td>Mode 1</td>
<td>Effect 1</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Effect 2</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Mode 2</td>
<td>Effect 1</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Effect 2</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Effect 3</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Section 2</td>
<td></td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

3. **Bow-tie Analysis (BTA):** BTA (Iannacchione et al., 2007c) combines the evaluation of the likelihood of a hazard, reliability of hazard mitigation measures, and reliability of recovery measures should an incident occur and the consequences if the recovery measures fail as well. Given the extent of the assessment, Bow-tie Analysis is preferred in the analysis of major/catastrophic failures such as mine explosions (McAteer et al., 2011), subsidence, or flooding and can be used for large-scale and hazard-specific risk identification.

4. **Fault Tree – Event Tree Analysis (FTA – ETA):** FTA – ETA (Iverson et al., 2001, Lacasse et al., 2008) is similar to Bow-tie Analysis in terms of combining the detailed evaluation of both the likelihood and consequences of the hazard. The key difference from Bow Tie Analysis, however, is that the emphasis on calculating the numerical probabilities of both the likelihood and consequences is built into the system. FTA-ETA focus on a particular hazard and breaks it down to its root causes. It is therefore suited for small-scale and hazard-specific risk identification. FTA-ETA is discussed in detail in the next chapter as a way of carrying out quantitative geotechnical risk assessments in mines. Table 9 shows a summary of appropriate tools on the basis of GRA elements.
### 4.3 Risk assessment parameters

Risk assessments can be carried out both qualitatively and quantitatively, depending on the amount of information and resources available and the level of accuracy needed for the risk assessment (Brown, 2012). Qualitative risk assessment parameters are expressed descriptively, with the likelihood of a hazard ranging from very high to very low and the consequences of the hazard ranging from minor to catastrophic. Qualitative terms are good for communicating the current risk among the workforce and to a non-expert. A qualitative description of the likelihood, consequences, and risk can often be a necessity in the event of a lack of historical evidence or data (Publication 2).

Quantitative parameters involve representing the likelihood, consequences, and risk with a numerical value such as the number of events per year, percentage probability, total potential financial loss in dollars/euros, etc. Quantification enables detailed risk analysis and adopting effective mitigation measures. Quantitative parameters enable the calculation of the total potential loss arising from a hazard, which can then be used in justifying expenditure on mitigation. Quantitative parameters also allow the integration of mine site instrumentation, historical data, and periodic observations into a real-time or near-real-time risk assessment. Table 10 shows the recommended risk assessment parameters for different stages of risk assessment.

<table>
<thead>
<tr>
<th>Geotechnical Data</th>
<th>Stage of Risk Assessment</th>
<th>GRA Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Pre-feasibility</td>
<td>Qualitative</td>
</tr>
<tr>
<td>Intermediate</td>
<td>Bankable Feasibility</td>
<td>Quantitative (Qualitative for large mine sections)</td>
</tr>
<tr>
<td>High</td>
<td>Mine Planning and Operation</td>
<td>Quantitative</td>
</tr>
</tbody>
</table>

### 4.4 Risk assessment approach

The risk assessment approach is the most significant part of a risk assessment as it deals with converting identified hazards into potential risks. In a risk-based design approach, risk assessments can lead to the selection or rejection of one method and therefore the assessment is required to be accurate. Risk assessment approaches can be further divided into the following three subcategories (Publication 2).
1. **Deterministic approach:** A deterministic approach to risk assessment is to measure the hazard symptoms directly and draw likelihood conclusions from that. Extensive geotechnical instrumentation and thus resources are required to cover a large area. Roof fall risk assessment using roof convergence measurement is an example of a deterministic approach. Tolerances can be set through modelling or historical data to convergence readings, which can in turn be used to assign risk scores to the mining areas.

2. **Probabilistic approach:** A probabilistic approach takes into account the underlying variability and uncertainty in geotechnical data (Ang and Tang, 1984). The variability of recorded data can be summarised either by using a probability distribution function such as Normal, Weibull, Poisson distribution, etc., or can be summarised as a single value, such as a 50% chance of over mining leading to the collapse of a pillar. A probabilistic approach can be used to break down a hazard into its underlying causes and each cause can then be assigned a probability value. For example, the roof fall hazard can be further broken down to weak strata, groundwater seepage, the shape and size of the opening, pillar strength, mining sequence, etc. Probability values can be assigned to each of the sub-causes using historical frequencies, current observations, or expert opinions in the absence of sufficient data. The interactions between the underlying causes as regards the final hazard can be modelled either by using frequentist interpretations such as Monte Carlo simulations or by using Bayesian interpretation using Bayesian networks (Kelly and Smith, 2009). Probabilistic methods work well with large amounts of data and historical evidence. However, in the absence of data, expert opinions can be used to obtain an estimate of likelihood and consequences.

3. **Possibilistic approach:** A possibilistic approach uses established empirical methods such as Q (Barton, 1987), RMR (Bieniawski, 1989), or RFRI (Iannacchione et al., 2007b) and translates them into risk values. For example, the Roof Fall Risk Index (RFRI) method uses multiple roof fall parameters such as the roof bedding thickness, groundwater, etc. and assigns a numerical score to each parameter. The cumulative value of all the scores is converted into RFRI value, which in turn is used to classify the area into high/low roof fall risk. Given that empirical methods are created by using data from several mines, a possibilistic approach enables quick risk assessments through inspections and simple geotechnical data gathering through geotechnical mapping. However, it requires the development of separate methods for individual hazards such as stope collapses, strain-burst, roof collapses, flooding, etc.

4.5 **Selection of risk assessment approach**

Once the type of geotechnical risk assessment (GRA) and risk assessment parameters for the risk assessment have been selected, the next step is to choose
between deterministic, probabilistic, and possibilistic methods for the risk assessment. A numerical ranking system was developed for this purpose (Publication 2). Each category described earlier as part of the scope of the GRA is assigned a numerical weight corresponding to deterministic (De), probabilistic (Pr), and possibilistic (Po) methods on the basis of their suitability. Figure 3 shows a blank ranking form. Once the appropriate element for the GRA in question is selected, its weighted values are transferred to the empty cells to the left.

Figure 3. Numerical Ranking form for GRA. (Modified after Publication 2)
Let us consider the example of a geotechnical risk assessment planned to be conducted for a primary access tunnel in an underground mine. In this case it is assumed that additional shotcreting and cable bolting were carried out to mitigate the risk of a range of geotechnical incidents such as a strainburst, roof collapse, or spalling etc. in the tunnel. The various boxes in the numerical ranking form in Figure 3 will be filled in using the following logic.

1) **GRA Type: Proactive, Reactive, or Change implementation:** The planned GRA is to evaluate the performance of cable bolts in an already-excavated drift. Therefore, the ‘Routine’ box is selected and its risk assessment approach scores, i.e. the possibilistic (Po), probabilistic (Pr), and deterministic (De) values, are transferred to the ‘Reactive’ box and eventually to the ‘GRA’ type box. The ‘Routine’ box is appropriate here as the GRA is not being performed for a planned excavation (Proactive), nor in response to failure symptoms (Reactive -> Symptom) and not because some design changes are being made to the drift (Change Imp.).

2) **GRA Area: Scale of operation:** The GRA is being carried out for a large primary drift. Therefore, the ‘Large’ box should be selected and its risk assessment approach score should be transferred to the ‘GRA Area’ box.

3) **GRA Hazard Scope: Hazard-specific or site-specific:** Given that the GRA is being conducted for all the multiple geotechnical risks and not a specific hazard, the ‘Site-sp.’ box should be selected and its contents should be transferred to the ‘GRA Hazard Scope’ box.

4) **Reporting Requirement: For external or internal users:** It is assumed that the GRA is being conducted for internal use among the workforce. Therefore, the ‘Internal’ box should be selected and the contents transferred to the ‘Reporting’ requirement box.

5) **Resources available to conduct the GRA:** It is assumed that sufficient manpower is available to carry out the GRA. Instrumentation has been planned to measure stresses. However, no historical data is available for collapses in a similar tunnel. Therefore, the ‘Average’ box is selected and its contents are transferred to the ‘Resource available’ box.

The contents of the final five boxes listed above are then added to arrive at an overall score for possibilistic (Po), probabilistic (Pr), and deterministic (De) approaches. The approach with the highest numerical score is the recommended approach for GRA. Figure 4 shows the completed numerical ranking form with the above example, where the shaded boxes represent the elements chosen when deciding the numerical rank. While the selection criteria and numerical weights are subjective, it is intended to form the starting point for formal geotechnical risk assessment. The numerical scores can be adjusted to meet the local site conditions and expertise. When completed, the same form can be used as a quick summary of the scope of the risk assessment (Janiszewski, 2014).
Figure 4. Example of a completed GRA form with shaded cells showing elements used in the ranking. (Modified after Publication 2)
5. Probabilistic risk assessment using frequentist and Bayesian Interpretations

The risk assessment approach describes the way in which the likelihood and consequence of a hazard are evaluated to represent risk. This leads to the estimation of the risk level, which in turn decides whether the risk can be afforded in its current state or additional efforts need to be put in place to mitigate them. In principle, this decides if action needs to be taken following the risk assessment and, if so, what. Of the three approaches mentioned in the previous chapter, namely deterministic, probabilistic, and possibilistic approaches, probabilistic risk assessment is widely used for quantifying risk. This chapter explains the use of probability in quantifying risk by using a stope collapse (Publication 4), strainburst, and spalling as examples (Publication 5). Two types of probabilistic reasoning were used to forecast the risk. The first method is frequentist reasoning, which uses a maximum likelihood estimate from observed data to determine probabilities. Frequentist reasoning has been demonstrated through the use of Fault Tree and Event Tree Analysis of a strainburst in an underground mine (Publication 3). The second method uses Bayesian reasoning, which combines data and prior beliefs to arrive at the risk of spalling using Bayesian networks.

5.1 Strainburst likelihood analysis using a fault tree

Fault Tree Analysis (FTA) consists of systematically deconstructing an event into its underlying causes and assigning probabilities to each cause (Iverson et al., 2001). FTA consists of three elements. The first element is called the ‘Top event’, which is the primary incident being assessed, which in this case is a strainburst in an underground mine. The second element is ‘Hazards’, which are the underlying causes of the top event. The third is ‘Boolean gates’, which define the relationship between hazards and the top event in the form of ‘and’ and ‘or’ gates. A hazard can in itself have its own causes and sub-causes. The Fault Tree Analysis is repeated until the fundamental cause of the incident is found. The fundamental causes are assigned probability values and these values in turn give the likelihood of the top event. This method helps in addressing the root cause of the problem instead of treating symptoms. Figure 5 shows
a completed fault tree for the strainburst example with assumed data (Publication 3).

The process of a strainburst in an underground mine has been divided into failure-causing elements and failure-resisting elements. Failure-causing elements evaluate the intermediate hazards and their probabilities. Failure-resisting elements evaluate the failure of elements that are generally put into place to prevent the hazard. For instance, natural and artificial support in an underground mine helps prevent a strainburst. Sub-standard support may not provide enough stress relief to prevent a strainburst and is therefore listed under failure-resisting elements. The likelihood of a strainburst depends on the hardness of the rock and the stresses acting on it. While rock hardness is an intrinsic property that is taken into account in mine design, the potential stresses acting on the rock mass need to be subjected to systematic evaluation. Mining stresses are further divided into stresses induced by mining activity and stresses induced by natural causes such as seismicity. Mining-induced stresses are broken down to their primary causes, such as poor excavation/pillar shape, an incorrect mining sequence, stresses induced by blasting/mine-induced seismicity, and loading by geological structures. A strainburst occurring as a result of poor support is divided into artificial and natural support. Poor artificial support results from incorrect support design, inferior-quality reinforcements, and incorrect installation practices. Poor natural support results from poor quality of the rock or the presence of previously unknown faults or fractures. The human error is common to the evaluation of both failure-causing and failure-resisting elements.
Once the intermediate hazards and root causes were identified, the next step was to assign probabilities to root causes and to define the relationships between the root cause, intermediate hazard, and top hazard using ‘and’ and ‘or’ Boolean gates. Probability values can be assigned using historical data when this is available. In the absence of historical data, nominal probability values can be assigned through consultation with field experts. For example, the probability of reinforcements being of inferior quality can be obtained through random destructive tests on samples of roof bolts, shotcrete, wire mesh, etc. When such data is not available, the reinforcement crew can provide a nominal value based on their experience in the field. An ‘and’ gate is used to define the relationship between a primary and intermediate hazard. An ‘and’ gate implies that all the primary hazards need to be realised to cause an intermediate or top hazard. An ‘or’ gate is used when any of the primary hazards can cause an intermediate or top hazard.

While the probability of primary hazards is obtained through data collection, the probability of intermediate and top hazards is solved using laws of probability. When an intermediate hazard such as ‘poor natural support’ is connected to the primary hazard using an ‘or’ gate, its probability is obtained using the rule of addition as per Equation (5) below (Walpole and Myers, 1993):

\[
P(Poor\ natural\ support) = P(Poor\ rock\ quality\ data \cup \ Presence\ of\ faults \cup Human\ Error) = 1 - ((1 - 0.05) \times (1 - 0.05) \times (1 - 0.1)) = 0.188
\]

Figure 5 uses an ‘or’ gate to show that in the absence of a warning system, any of the intermediate hazards can cause a strainburst. In the absence of a warning system, solving all the probability values in line with Equation (5) results in a final strainburst probability of 61%. However, when a warning system is put in place, it has to fail with the intermediate hazards for a strainburst to happen and therefore uses an ‘and’ gate. The probability of an intermediate or top hazard, when connected by an ‘and’ gate, is obtained by multiplying the underlying probabilities. The probability of a strainburst with a warning system is therefore reduced to \(61\% \times 0.2 = 12.2\%\). A mining company may decide that a risk level of 12.2% is either tolerable or put additional mitigation measures in place to reduce the risk even further. The concept of tolerable and intolerable risk is discussed further in Chapter 7.

### 5.2 Strainburst consequence analysis using an event tree

An event tree describes the various consequences that can occur following the realisation of the top hazard (Andrews and Dunnett, 2000). Each subsequent consequence is evaluated for the probability of its either happening or not happening. In the case of a strainburst, there is a potential for harm to personnel, damage to property, and loss of production. In this assessment, only the short-term consequences are evaluated. Long-term consequences such as a
drop in the share value or intangible consequences such as loss of employee morale, negative stakeholder perception, etc. are excluded. The probability calculations in the event tree are mainly performed through consultation, as there may not be sufficient information available on all the possible outcomes arising from an accident. It is advised to err on the conservative side when estimating consequences as the primary aim of risk assessments is to prevent hazards becoming incidents.

Table 11. Risk assessment parameter recommendation-based GRA stage

<table>
<thead>
<tr>
<th>Strainburst (receives probability from Fault Tree)</th>
<th>Manned Shift</th>
<th>Injury</th>
<th>Fatality</th>
<th>Property Loss</th>
<th>Production Loss</th>
<th>Outcome</th>
<th>P (Outcome)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>H - 0.7</td>
<td>H - 0.6</td>
<td>H - 0.5</td>
<td>H - 0.65</td>
<td>H - 0.4</td>
<td>a1</td>
<td>5%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>NH - 0.35</td>
<td>NH - 0.6</td>
<td>a2</td>
<td>14%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>NH - 0.35</td>
<td>a3</td>
<td>21%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>NH - 0.5</td>
<td>H - 0.4</td>
<td>a4</td>
<td>11%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>NH - 0.6</td>
<td>a5</td>
<td>27%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>NH - 0.35</td>
<td>a6</td>
<td>42%</td>
</tr>
<tr>
<td></td>
<td>NH - 0.4</td>
<td>H - 0.6</td>
<td>H - 0.5</td>
<td>H - 0.65</td>
<td>H - 0.4</td>
<td>a7</td>
<td>18%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>NH - 0.35</td>
<td>NH - 0.6</td>
<td>a8</td>
<td>46%</td>
</tr>
<tr>
<td></td>
<td>NH - 0.3</td>
<td>H - 0.8</td>
<td>H - 0.5</td>
<td>H - 0.6</td>
<td>H - 0.4</td>
<td>a9</td>
<td>14%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>NH - 0.4</td>
<td>NH - 0.4</td>
<td>a10</td>
<td>24%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>NH - 0.2</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 11 shows a completed event tree following a strainburst with assumed data (Publication 3). The prefix H implies that the event will happen, while NH implies that the event will not happen. The probabilities of combinations of consequences were obtained by multiplying the values along the branches. The outcome column in Table 11 shows the ten combinations of consequences that were evaluated following a strainburst. Outcome a1 was obtained by multiplying the probability values along the branches and was calculated to be \((0.7 \times 0.6 \times 0.5 \times 0.65 \times 0.4) = 5\%\). ‘a1’ therefore represents a 5% chance that a strainburst will result in an injury, a fatality, property loss, and production loss.

5.3 Likelihood and consequence analysis using a Bayesian network

Bayesian networks are based on Bayes’ theorem (Bayes, 1763) and define the conditional relationship between two or more variables as defined in Equation (6).

\[
P(H_i|E) = \frac{P(E|H_i) \times P(H_i)}{P(E)} \tag{6}
\]

where \(P(H_i|E)\) is the posterior probability of a hypothesis (H) being true, given the evidence (E). \(P(E|H_i)\) is the probability of the evidence if the hypothesis
was true. \( P(H_1) \) is the prior probability or belief in the hypothesis and \( P(E) \) is the probability of the evidence. Figure 6 shows an example of a Bayesian network modified from work done by Smith (2006)(2006)(2006)

![Bayesian Network Diagram](image)

**Figure 6. Example of a completed GRA form with shaded cells showing elements used in the ranking. (Publication 4, modified after Smith, 2006)**

The hypothesis nodes are denoted by \( H_1 \) and \( H_2 \), while the evidence node is denoted by \( E \). In general terminology, the nodes at the origin of the arrow are referred as the parent node (\( H_1, H_2 \)), while the node at the end of the arrow is referred as the child node (\( E \)). The solid arrows, along with the nodes, form the causal model. If the fault tree example from Section 5.1 is to be re-created using Bayesian networks, the top hazard, the strainburst would be the evidence, while the stresses acting on the rock and rock quality would be the two hypothesis nodes. The frequentist interpretations using a fault tree involves assigning a fixed probability value to rock strength and stresses. However, when the same nodes are being used in a Bayesian network, it is assumed that the probability itself is a random variable and it is therefore represented using a probability distribution. Therefore, the rock strength and stress nodes in a Bayesian network (BN) are represented using a probability distribution such as normal, Poisson, Gaussian, etc. instead of a fixed value.

A Bayesian network enables comprehensive modelling of the causation of an incident as the relationships between the hazards need not be unidirectional. For instance, poor excavation shape and blasting/seismicity are shown to have an impact on mining-induced stress as per the fault tree. However, poor excavation design can increase the risk of blasting-induced seismicity and they therefore also affect each other. While this can easily be modelled in BN, a
fault tree connection would require the creation of another intermediate hazard of poor excavation shape below blasting/seismicity. Bayesian networks can be used to obtain both forward and backward inferences (Fenton and Neil, 2012). A forward inference refers to the calculation of the probability of a strainburst when the intermediate hazard probabilities are known. A backward inference refers to the back-calculation of intermediate hazard probabilities after using strainburst probabilities. A fault tree, however, can only be used in forward inference to calculate the probability of a strainburst from the intermediate hazard probabilities.

5.3.1 Spalling depth forecasting using a fault tree and frequentist interpretation

This section uses spalling depth as an example to demonstrate the difference between the frequentist and Bayesian interpretations of risk (Publication 5). The Olkiluoto nuclear waste disposal case data (Siren et al., 2011) has been used to calculate the spalling depth. The spalling depth in an underground opening can be calculated using Equation (7) (Martin and Christiansson, 2009):

\[ S_d = a \left( \frac{0.5}{FOS} - 0.52 \pm 0.1 \right) \]  

where \( S_d \) is the spalling depth in metres, \( a \) is the tunnel radius, \( 0.52 \pm 0.1 \) is an empirical factor, and FOS is the factor of safety against spalling. FOS can be calculated using Equation (8) below:

\[ FOS = \frac{\sigma_{sm}}{\sigma_{\theta\theta}} \]  

where \( \sigma_{sm} \) is the rock spalling strength and \( \sigma_{\theta\theta} \) is the tangential stress at the rock surface. Since a frequentist estimate works with a single value of probabilities, spalling risk estimates need to be performed for individual spalling depth values. For this case, it is assumed that a spalling depth of 0.1 m or more is considered intolerable using a mean empirical factor of 0.52. Using Equations (7) and (8), the spalling depth will be more than 0.1 m if the tangential stress is more than 69 MPa and the rock spalling strength is less than 64 MPa. Data collected from the Olkiluoto site indicated that the Uniaxial Compressive Strength (UCS) of the rock had a mean of 115 MPa with a standard deviation of 23 MPa (Posiva, 2009). The rock spalling strength can be obtained from the UCS by multiplying it by a scale factor \( k \) and it is assumed to be \( 0.57 \pm 0.02 \) for crystalline rock (Martin and Christiansson, 2009). The tangential stress can be obtained from the principle stress using the Kirsch equation below:

\[ \sigma_{\theta\theta} = A\sigma_1 - \sigma_3 \]  

where \( \sigma_1 \) and \( \sigma_3 \) are the major horizontal and minor vertical stresses respectively. \( A \) is the shape factor, with a median value of 2.6 for the site (Siren et al.,
Table 12 below shows the 10% fractile, 90% fractile, and mean value for $\sigma_1$ and $\sigma_3$ as obtained from Olkiluoto.

**Table 12. Major horizontal stress and minor vertical stress for Olkiluoto at a depth of 400 m (Siren et al., 2011)**

<table>
<thead>
<tr>
<th>Variable parameter</th>
<th>Lower Bound 10%</th>
<th>Upper Bound 90%</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Major horizontal stress, $\sigma_1$ [MPa]</td>
<td>19.6</td>
<td>31.6</td>
<td>25.6</td>
</tr>
<tr>
<td>Minor vertical stress, $\sigma_3$ [MPa]</td>
<td>9.6</td>
<td>11.7</td>
<td>10.6</td>
</tr>
</tbody>
</table>

Figure 7 shows the fault tree diagram for a spalling depth > 0.1 m at Olkiluoto using the rock spalling strength $\sigma_{sm}$ and tangential stress $\sigma_{gb}$ probabilities obtained from the site. The likelihood of the spalling depth being greater than 0.1 m was calculated to be 5% × 2% = 1%. One of the key disadvantages of this method is that the risk of the spalling depth will need to be revalued for any spalling depth value other than 0.1 m or a different combination of $\sigma_{sm}$, $\sigma_{gb}$, and the empirical factor.

**Figure 7. Fault tree diagram for spalling depth greater than 0.1 m at Olkiluoto**

### 5.3.2 Forecasting spalling depth using a Bayesian network

Bayesian networks overcome the challenge of variability in data across multiple variables by incorporating the full probability distribution in the calculation as prior probabilities instead of single values (Publication 5). Equation (7) can be expanded using Equations (8) and (9), as shown in Equation (10):

$$ S_d = a \left(0.5 \frac{\Delta \sigma_1 - \sigma_3}{UCS \ k} - 0.52 \pm 0.1 \right) $$

In order to solve the above equation using a Bayesian network, the variables $\sigma_1$, $\sigma_3$, and $k$ were treated as prior nodes. Mean uniaxial compressive strength (UCS) was used instead of the distribution, as suggested by Martin and Christansson (2009). $\sigma_1$ and $\sigma_3$ were defined with a prior triangular distribution using values from Table 12 and $k$ was defined using a triangular distribution with a lower limit of 0.55, mode of 0.57, and upper limit of 0.59. The BN was solved for the calculation of the factor of safety (FOS), probability of fail-
ure (POF), and probability of various spalling depths. The model predicted a 7.7% chance that the FOS value would be less than 1, resulting in some form of spalling. Convention calculation using mean values for UCS, $\sigma_1$, $\sigma_3$, and $k$, results in an FOS value of 1.17. While FOS values can be converted into the probability of failure (POF) using prescribed tables (Galvin et al., 1999), this does not directly give a meaningful description of how likely the failure is. The solved BN can provide the probability of failure values for all possible spalling depths and can include additional uncertain variables such as stress orientation and the correlation between stress and rock mass strength without having a significant impact on computational time. Figure 8 shows a completed Bayesian network to calculate the spalling depth at Olkiluoto.
Consequence modelling in a Bayesian network is identical to likelihood modelling, where the causes and effects of various consequences arising from spalling can be modelled using nodes. Alternatively, each spalling depth can be assigned an associated financial loss value in order to arrive at the total potential financial loss at current risk levels. If additional nodes are used to model consequences, likelihood and consequence assessment can be combined in a single Bayesian network to model the entire risk. Once a network is built, the prior probabilities can be updated as additional data becomes available.

5.4 Expert opinion-based risk forecasting using a Bayesian network

Bayesian network-based risk assessment has the advantage of being able to work with expert opinions in the absence of data. Expert opinions can be obtained through systematic interviews to determine the causal factors behind an accident. Structured interviews with questionnaire were carried out in an underground metal mine in Finland to determine the causes influencing stope collapse (Publication 4). The mine used a subjective risk assessment method in which the rock mechanical engineer assigned a risk score between 1 and 3 on the basis of his experience in the mine with respect to stope collapse. The mine experienced four to six large collapses per year, with partial collapses occurring as frequently as 10 to 12 times per month. The interviews determined 10 potential factors which influenced stope collapse, as listed below:

1) Presence of geological structure: geological structures such as faults and fractures were considered the main cause of stope collapse by all the experts;
2) Rock strength and brittleness of rock: brittle rock, despite being competent in GSI values (Hoek, 1994, Marinos et al., 2005), was prone to stope collapse;
3) Stress field around the stope: stress was considered a contributor, particularly when the stope was near existing open pit operations;
4) Presence of groundwater: groundwater was considered a cause of stope collapse when discontinuities had chalk fillings. Overall, it was not a common cause of collapses;
5) Transition zones between ore and waste: transition zones were considered to make a stope collapse likely;
6) Mining sequence: only a few experts considered that error in the mining sequence had the potential to cause a collapse. However, it was not considered a common cause;
7) Open time and span of excavation: long and wide stopes were found to be more prone to collapse compared to narrow stopes. The problem becomes worse for stopes that have been standing for a long time;
8) Blasting activity around stope: blasting was considered a potential cause, especially with a high charge density;
9) Stability of neighbouring stope: the collapse of a neighbouring stope was considered a strong indicator for the collapse of the current stope;
10) Ground movement: ground movement was considered as a strong indicator of stope collapse.

5.4.1 Stope collapse forecasting using interview data and a Bayesian network

The ten contributors identified from the interview were grouped into three sub-categories to simplify the computational requirements of the Bayesian network and reduce the size of the conditional probability tables. The subcategories were: ‘Rock mass characteristics’, which combine transition zone, rock mass strength, groundwater, and geology; ‘Mining-induced’, which combines mining sequence, blasting, stress field, and excavation span, and ‘Failure symptom’, which combined ground movement and the stability of the neighbouring stope. The nodes were assigned Boolean states of “Yes” and “No”, with “Yes” implying that the node caused a stope collapse and “No” implying that the node did not cause a stope collapse. For instance, a “Yes” value for the node ‘Stress field’ implies the presence of a stress field that can cause a collapse, while “No” implies the stress field is not large enough to cause a collapse. The prior probabilities for the parent nodes were assumed for demonstration purposes. The conditional probabilities for the child nodes were defined using guidance from the interview process. The prior probabilities for parent nodes (the nodes from where the arrows originate) are shown in the figure. Table 13 shows the conditional probability table, which defines the relationship between the parent and child nodes for all child nodes except ‘Stope collapse’. Artificial nodes such as ‘groundwater and geology’ and ‘span and stress’ were created to reduce the number of parent nodes reporting to a single child node and thus reduce the complexity of the conditional probability tables. For example, the first entry of 80% in the table means that in the presence of adverse geological structure and groundwater, there is an 80% chance of the two nodes contributing to a stope collapse. The second entry of 60% implies that in the presence of geological structure and absence of groundwater, the probability drops to 60%. The third entry suggests that the probability of groundwater and geological structure contributing to a stope collapse drops to 20% in the absence of an adverse geological structure but presence of groundwater. This was in line with the general opinion in the mine that geological structure was more likely to contribute to a stope collapse in comparison to groundwater.
Table 13. Conditional probability table for all child nodes used in the Bayesian network shown in Figure 9

<table>
<thead>
<tr>
<th>CPT for node</th>
<th>Node</th>
<th>Node states</th>
</tr>
</thead>
<tbody>
<tr>
<td>Groundwater and geology</td>
<td>Geological structure</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Groundwater</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>80%</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>20%</td>
</tr>
<tr>
<td>Rock mass characteristics</td>
<td>Groundwater and geology</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Rock strength</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>95%</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>5%</td>
</tr>
<tr>
<td>Span and stress</td>
<td>Excavation span and time</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Stress field</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>95%</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>5%</td>
</tr>
<tr>
<td>Mining-induced</td>
<td>Span and stress</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Blasting</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Mining sequence</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>95%</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>5%</td>
</tr>
<tr>
<td>Failure symptom</td>
<td>Ground movement</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Neighbouring stope</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>99%</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>1%</td>
</tr>
</tbody>
</table>

The conditional relationship between the final stope collapse node and the three subcategories was defined using a NoisyOr function (Diez, 1993) as shown in Equation (11). The NoisyOr function represents the potential contribution of the subcategories towards a stope collapse. A fourth category, ‘Leak’, was added to the stope collapse, which represents the missing or unknown factors not modelled in the Bayesian network. Figure 9 shows the complete Bayesian network for forecasting a stope collapse.

\[
P(\text{Stope collapse}) = \text{NoisyOr}\left(\begin{array}{c}
\text{Rock mass} \\
\text{Mining induced} \\
\text{Failure symptom} \\
\text{Leak}
\end{array}\right)\]  

(11)
The probability values for the child nodes: ‘rock mass characteristic’, ‘failure symptom’, ‘mining-induced’, ‘span and stress’, and ‘groundwater and geology’ shown in Figure 9 are the marginal probability values obtained through the process of marginalisation (Spiegelhalter and Lauritzen, 1990). As the number of parent nodes increases beyond two, the annual calculation of probabilities can be difficult and error-prone. The BN in Figure 9 was therefore solved using the Agena Risk software (Agena, 2017). The prior probabilities and conditional probabilities from Table 13 and the conditional probability from Equation (11) were assigned for the respective nodes in Agena Risk and the Bayesian network was solved (Publication 4). The marginal probability of a stope collapse in Figure 9 indicates that there is a 37% chance of a stope collapse in the mine without any additional inputs entered into the BN. This BN can now be updated with stope-specific data. For instance, if it is discovered that the neighbouring stope has had a collapse, its prior probability can be updated from 5% to 100%. Solving the BN with the new priors revises the stope collapse probability from 37% to 53%.

5.4.2 Calibrating stope collapse forecast using instrumentation data

The outcome of the BN shown in Figure 9 depends on the prior probabilities and conditional probabilities used. The conditional relationship as defined by the experts can be prone to human error. Bayesian network-based risk assessments can be updated with every passing stope collapse incident. Whenever a stope collapse incident happens, the prior probability of the stope collapse node is updated to 100%. Solving the BN now updates the probability of all the nodes through backward inference and Bayes’ theorem (Equation 6). These probabilities can now be verified using incident investigations. For example,
the current BN assumes a small chance of groundwater influencing stope collapse according to the expert interviews. However, with every passing stope collapse, if groundwater is discovered to be a prominent cause, its impact on stope collapse can be increased.

The disadvantage of model calibration using incident investigation is that it can take a long time and during this period, the mine can suffer severe losses (Publication 4). This can be addressed with the use of data from instrumentation, such as ground movement monitoring using extensometers. Extensometers with the capability of real-time data transfer can be installed on a few selected stopes. Thresholds can be set on ground movement readings to represent various levels of risks. These levels can be identified either by carrying out a controlled collapse of a mined-out stope or through numerical modelling. Bayesian networks offer the capability of replacing finite observations such as the presence or absence of features with partial probability values. These values are referred to as ‘soft evidence’ (Fenton and Neil, 2012). Table 14 shows an example of ranges of extensometer readings and their associated probability of stope collapse values.

Table 14. Example of extensometer reading range and their associated probability values (soft evidence) for stope collapse

<table>
<thead>
<tr>
<th>Real-time ground movement data (mm/day)</th>
<th>Probability of stope collapse</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 to 3</td>
<td>60%</td>
</tr>
<tr>
<td>4 to 10</td>
<td>80%</td>
</tr>
<tr>
<td>&gt; 10</td>
<td>95%</td>
</tr>
</tbody>
</table>

Figure 10 shows the modified BN with ‘Real-time extensometer data’ replacing the ‘Failure symptom’ node. The ‘Failure symptom’ node was a replacement as it caters for ground movement and does not rely on the history of the neighbouring stopes to evaluate the current stope ground movement. Figure 10 shows the solved BN for an assumed extensometer reading of 7 mm/day. On the basis of Table 14, 7 mm/day corresponds to a stope collapse probability of 80%. This value is then assigned as soft evidence to the stope collapse node. Solving the BN updates all the nodes showing the likely posterior probabilities of all nodes, which would result in a stope collapse probability of 80%. These updated values are shown in Figure 10. These values can now either be verified as being true or adjusted on the basis of site investigation findings.
Figure 10. Stope collapse BN example solved using real-time data and soft evidence using backward inference. (Publication 4)
6. Learning from data using Bayesian network for risk assessment

Bayesian networks offer the capability of learning from historical data to create appropriate probability distributions that best fit the data. This can be used in creating an incident forecast if a mine has been collecting incident frequency information over the previous years. Learning from data can also be applied to any statistical parameter, such as rock strength, stress distributions, joint set, etc., which can then be used in a causal model to assess risk. This chapter uses roof fall incident data collected by the Mine Safety and Health Administration (MSHA) across 12 mines in the Appalachian region of the United States of America between 1979 and 1997 (Anon, 2000) to forecast future incidents (Publication 5). This data was analysed in the past through curve fitting frequency data into probability distributions to make roof fall forecasts (Duzgun and Einstein, 2004). A hybrid model combining a data-driven incident forecast with the use of multiple probability distributions is also proposed as a risk assessment strategy.

6.1 Parameter learning on roof fall data

Incident information collected from the mines was anonymised by assigning each mine a seven-digit numerical code (Anon, 2000). To demonstrate the parameter learning capabilities of a Bayesian network (BN), incident data from mine 4601816, with 154 roof fall incidents, was used. Figure 11 shows the annual roof fall frequency (NOF) for mine 4601816. Duzgun and Einstein (2004) proposed the use of Poisson distribution over 1141 sets of roof fall incident data across 12 coal mines in the USA over 19 years to forecast future roof fall incidents. Poisson distribution is a single variable probability distribution which can be used to define the number of roof falls per year (NOF) as shown in Equation (12).

\[
P(\text{NOF}) = e^{-\lambda} \times (\lambda^{\text{NOF}} / \text{NOF}!)
\]

where \(P(\text{NOF})\) is the probability of annual roof fall frequency and \(\lambda\) is the Poisson parameter which is equal to the mean of the sample population. \(\lambda\) for mine 4601816 was calculated to be 5.68. The frequentist forecast of a roof fall in
later years uses a single value of $\lambda$ as 5.68 to plot a probability distribution curve using Equation (12). A Bayesian approach to incident forecasting involves treating $\lambda$ itself as an uncertain variable with a prior probability distribution. Parameter learning using Bayesian networks can then be used to obtain an appropriate probability distribution curve for $\lambda$. Figure 12 shows a parameter learning BN which uses historical annual incident frequencies to learn the distribution of $\lambda$ and then use the learned distribution to forecast future incidents.

**Figure 11.** Annual roof fall frequency histogram for mine 4601816 (Anon, 2000).

**Figure 12.** Parameter learning BN to learn $\lambda$ from observed roof falls. The probability distribution for $\lambda$ was revised from a prior uniform probability through parameter learning using actual roof fall data from years 1 to 19. ‘Y1 7’ refers to seven roof falls in year one. The revised $\lambda$ distribution is used to forecast the annual roof fall frequency (Forecasted NOF). (Publication 5)
The node ‘Lambda’ (\( \lambda \)) was assigned a uniform probability distribution between 0 and 20. 20 was chosen as an upper limit as the annual roof fall frequency never exceeded 20 in the last 19 years in any of the mines for which the data was collected. Uniform priors are a good way to express unbiased probability when nothing is known about the prior probability. 19 child nodes named Y1 to Y19 were defined for the parent node \( \lambda \) (Figure 1). A 20th child node named ‘Forecasted NOF’ was defined to obtain the forecasted annual roof fall frequency (NOF). The relationship between the parent node ‘Lambda’, child nodes Y1-Y19, and child node ‘Forecasted NOF’ was defined using the Poisson distribution equation as shown in Equation (12). Once the BN was completed, actual roof fall data as observed in the last 19 years in mine 4601816 was entered into the child nodes as evidence. For instance, the entry ‘Y1 7’ in Figure 12 refers to seven roof falls in year one. When solving the BN, backward inference was performed on the parent node \( \lambda \) to learn from the data and revise its probability distribution. This revised posterior probability distribution was then used to solve the child node ‘Forecasted NOF’ to obtain the forecasted annual roof fall frequency. Figure 13 shows the comparison between the forecasted annual roof fall frequency generated through parameter learning, and the frequentist interpretation using a single value of \( \lambda \) (Publication 5). Although the Bayesian and frequentist interpretations yield nearly identical results, neither of the distribution curves fits the actual observed roof fall frequency well, as shown in Figure 13. Poisson distribution therefore may not be the best fit for Mine 4601816.

Figure 13. Frequentist Poisson vs. Bayesian Poisson comparison for forecasted annual roof fall frequency (NOF) probability for Mine 4601816. The x-axis represents the annual roof fall frequency (NOF), while the y-axis represents the probability distribution (PD). (Publication 5)

The roof fall data from Mine 4601816 was then modelled using a normal distribution. Unlike Poisson distribution, normal distribution is a two-variable distribution with mean and variance/standard deviation as two of its parameters. Parameter learning was again carried out with data from Mine 4601816 with mean and variance replacing \( \lambda \) as parent nodes. The mean and variance of
annual roof fall frequency (NOF) were assigned a uniform prior distribution ranging from 0 to 20 and 0 to 160 respectively. The forecasted annual roof fall frequency (NOF) normal distribution was truncated with a lower bound of 0 and upper bound of 20, thus creating a truncated normal distribution (Thompson, 1950). The completed BN and the forecasted annual roof fall (NOF) are shown in Figure 14. Figure 15 shows the comparison of the forecasted annual roof fall frequency using parameter learning with normal distribution, and annual roof fall frequency using a frequentist interpretation of Poisson distribution.

Figure 14. Parameter learning BN to learn mean and variance from observed roof falls. Mean and variance are first assigned a uniform prior probability. Their probability distribution is revised through parameter learning using actual roof fall data over 19 years. The revised distribution is used to forecast the annual roof fall frequency (Forecasted NOF). (Publication 5)
Figure 15. Frequentist Poisson vs. Bayesian normal comparison for the forecasted annual roof fall (NOF) probability for Mine 4601816. The x-axis represents the annual roof fall frequency (NOF), while the y-axis represents the probability distribution (PD). (Publication 5)

The relative error (E) of the forecasted value compared to actual observation was calculated using Equation (13) (ISO, 1993) for both Poisson and Normal distribution:

$$E = \sqrt{\frac{(P_n - RF_n)^2}{RF_n}}$$

where $E$ is the relative error in the forecasted data, $P_n$ is the forecasted probability of $n$ roof falls, and $RF_n$ is the relative frequency of $n$ roof falls as observed in historical data. Equation (13) resulted in an average relative error in the forecast of 49% when using a frequentist interpretation of the Poisson distribution. This error was reduced to 33% with the use of normal distribution as obtained with parameter learning in a BN (Publication 5).

6.2 Use of multiple distributions with a Bayesian network for incident forecasting

It is difficult to choose one distribution that best fits incidents across several mines or sections of mines. Mathematical validations such as the Chi-Square goodness of fit test can be used to test how well a distribution describes the data (Ang and Tang, 1984). These tests, however, use statistical parameters such as the mean, which is not directly observed in the population but is inferred from a sample population. Bayesian networks can be used to perform goodness of fit tests by evaluating the likelihood of historical data fitting a distribution. The goodness of fit test result is obtained by defining a parent node with possible probability distributions as the different node states. Figure 16 shows a BN used to carry out a goodness of fit test on data from Mine 4601816.
The parent node ‘possible distributions’ was assigned two states, Poisson and normal distribution, which were evaluated for their goodness of fit. Both the distributions were assigned a uniform prior probability of 50% each. 19 child nodes were added to the parent node to enter data from 19 years and a 20th node was added to forecast the annual roof fall probability distribution.

Unlike the previous parameter learning examples, where the child nodes and parent node were defined using either Poisson or normal distribution, the child nodes in this example are defined using a partitioned expression (Fenton and Neil, 2012), where both possible distributions are used to define the child nodes. Table 15 shows the conditional probability distributions used, along with their parameters in the child node. The Poisson and normal distribution parameters used in the table are statistical summaries of the distributions in Figure 15. The normal distribution was truncated using a lower bound of 0 and upper bound of 20, similar to the one in Figure 14.

<table>
<thead>
<tr>
<th>Possible distribution</th>
<th>Parameter used</th>
</tr>
</thead>
<tbody>
<tr>
<td>Truncated Normal</td>
<td>TNormal (5.75, 16.4, 0, 20)</td>
</tr>
<tr>
<td>Poisson</td>
<td>Poisson (5.68)</td>
</tr>
</tbody>
</table>

The results from the BN show that the observed data from Mine 4601816 had a 70% likelihood of being observed under normal distribution and a 30% likelihood of being observed under Poisson distribution (Figure 16). Normal distribution is therefore a better fit to describe the annual roof fall frequency in Mine 4601816. The forecasted annual roof fall frequency (Forecasted NOF) then applies the results of the goodness of fit test and weights the distribution 70% towards normal distribution and 30% towards Poisson distribution.

The data from all 12 mines was subjected to the goodness of fit test and the results from the test are shown in Table 16. Seven of the 12 mines were found
to be described better using normal distribution, while Poisson distribution was a better fit for five of the mines (Publication 5). Multiple distributions can similarly be used at the same time to generate an incident forecast weighted according to their goodness of fit results.

Table 16. Goodness of fit test results for frequentist Poisson and Bayesian normal distribution for annual roof fall frequency in 12 mines

<table>
<thead>
<tr>
<th>Mine ID</th>
<th>Poisson Parameter</th>
<th>Bayesian Normal Parameter</th>
<th>Probability of Observed Data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>λ</td>
<td>Mean</td>
<td>Variance</td>
</tr>
<tr>
<td>4601816</td>
<td>5.68</td>
<td>5.75</td>
<td>16.40</td>
</tr>
<tr>
<td>1502709</td>
<td>3.26</td>
<td>3.42</td>
<td>5.06</td>
</tr>
<tr>
<td>1503178</td>
<td>3.00</td>
<td>6.19</td>
<td>20.83</td>
</tr>
<tr>
<td>0100758</td>
<td>5.36</td>
<td>5.39</td>
<td>5.84</td>
</tr>
<tr>
<td>1502132</td>
<td>1.89</td>
<td>2.35</td>
<td>4.20</td>
</tr>
<tr>
<td>1502502</td>
<td>3.80</td>
<td>3.85</td>
<td>5.31</td>
</tr>
<tr>
<td>1504020</td>
<td>1.81</td>
<td>2.51</td>
<td>5.25</td>
</tr>
<tr>
<td>1512941</td>
<td>2.43</td>
<td>3.10</td>
<td>7.12</td>
</tr>
<tr>
<td>1513920</td>
<td>4.75</td>
<td>5.97</td>
<td>20.71</td>
</tr>
<tr>
<td>1514492</td>
<td>7.15</td>
<td>8.21</td>
<td>30.41</td>
</tr>
<tr>
<td>3600958</td>
<td>3.53</td>
<td>4.02</td>
<td>10.00</td>
</tr>
<tr>
<td>4605978</td>
<td>2.70</td>
<td>2.25</td>
<td>4.21</td>
</tr>
</tbody>
</table>
7. Risk representation and mitigation

Effective communication of risk to the stakeholders who are affected is as important as evaluating the risk. Given that the majority of the workforce are not involved in the risk assessment process, it is important that the communication is simple enough to be easily understood. For decision makers who plan mitigation measures to bring the risk level down, it is vital that the risk representation helps in tracking the effectiveness of the measures put in place. This chapter discusses risk representation and mitigation planning (Publication 3).

7.1 Defining risk levels

Geotechnical accidents have the potential to cause long-term damage to the mining operation, which can cause severe financial losses. It is therefore important that trigger thresholds are set by management which describe if the present level of risk is acceptable or not. The financial quantification of risk enables setting risk thresholds because it directly measures the impact a geotechnical incident will have on the business. This helps to justify how much additional money and resources can be spent on managing the risk and bringing the risk to financially acceptable levels. The strainburst example from Chapter 5 is used in this section to demonstrate risk thresholds and risk representation. Table 19 shows the various combinations of possible consequences as defined by the event tree in Table 11 and their probabilities.

<table>
<thead>
<tr>
<th>Manned Shift</th>
<th>Injury</th>
<th>Fatality</th>
<th>Property Loss</th>
<th>Production Loss</th>
<th>Outcomes</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>a1</td>
<td>5%</td>
</tr>
<tr>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>a2</td>
<td>14%</td>
</tr>
<tr>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td>a3</td>
<td></td>
<td>21%</td>
</tr>
<tr>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
<td>a4</td>
<td></td>
<td>11%</td>
</tr>
<tr>
<td>X</td>
<td></td>
<td>X</td>
<td></td>
<td>a5</td>
<td></td>
<td>27%</td>
</tr>
<tr>
<td>X</td>
<td></td>
<td></td>
<td>a6</td>
<td></td>
<td></td>
<td>42%</td>
</tr>
<tr>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td>a7</td>
<td></td>
<td>18%</td>
</tr>
<tr>
<td>X</td>
<td></td>
<td></td>
<td>a8</td>
<td></td>
<td></td>
<td>46%</td>
</tr>
<tr>
<td>X</td>
<td></td>
<td></td>
<td>a9</td>
<td></td>
<td></td>
<td>14%</td>
</tr>
<tr>
<td>X</td>
<td></td>
<td></td>
<td>a10</td>
<td></td>
<td></td>
<td>24%</td>
</tr>
</tbody>
</table>
Each of the consequences, namely injury, fatality, property loss, and production loss, can be assigned a nominal accident cost. The accident cost calculation can include tangible direct costs or long-term costs, which include the deterioration of the company’s reputation, loss of employee morale, etc. (Blumenstein et al., 2011). For this example, it is assumed that injury, fatality, property loss, and production loss cost on average €50,000, €500,000, €30,000, and €600,000 respectively. The next step to risk quantification is to define how great a financial loss arising from a geotechnical accident can be afforded by the company. This can be derived directly from the current cash flow of the company. Alternatively, a company can take a stringent position on the affordable financial risk despite being able to afford it as part of its commitment to the health, safety, and welfare of its employees and the environment.

Depending on the affordability of the risk, the risk can be divided into three levels. The first is called the objective risk level, which is the risk level an organisation should strive to achieve. The second is called intolerable risk. This is the risk level which is deemed intolerable by the company, and measures should be put in place to ensure that no risk exceeds this level. The third risk level is the risk between objective and intolerable risk and is known as tolerable risk. Tolerable risk defines the level of risk that the company can afford but every time a risk enters tolerable risk zone, mitigation measures need to be put in place to bring the risk level to the objective level.

### 7.2 Risk representation using a modified F-N diagram

FN diagram represents the frequency of an incident (F) and casualties from the incident (N) on a logarithmic scale (Pine, 2011). This diagram can be modified to replace casualties with the total financial loss resulting from an accident. Using the strainburst example from Chapter 5, section 5.1, the probability of a strainburst without a monitoring system was calculated to be 12.2%. This probability can be multiplied by the consequence probability obtained from the event tree outcome in Table 17 to obtain the total risk (Publication 3). For instance, the probability of outcome a1 is the product of the strainburst probability and probability of the event a1. In order to calculate the total financial risk, this probability can be multiplied by the financial loss resulting from individual outcomes. Outcome a1 comprises injury, fatality, property loss, and production loss. The nominal financial loss resulting from each of these consequences is defined in Section 7.1. Therefore, the frequency of outcome a1 is 60.9% x 5% = 3% and the total financial loss resulting from outcome a1 is €50,000 + €500,000 + €30,000 + €600,000 = €1,180,000. The frequency and total financial loss are calculated in a similar way for each potential outcome of the event tree.

In order to plot the outcomes in an FN diagram, one must define tolerable and intolerable risk. The tolerable and intolerable risk for the above example
are assumed to be €15,000 and €50,000 respectively. Figure 17 shows a completed FN diagram. The tolerable and intolerable risk levels are represented by the two straight lines in the graph.

![Modified FN diagram showing the probability of an event on the y-axis and the total financial loss on the x-axis on the basis of data from Table 17. The dashed enclosure shows the revised frequency of outcomes with real-time monitoring.](image)

Each outcome is plotted in the FN diagram. As can be seen from Figure 17, outcomes a3, a7, and a9 are beyond the intolerable risk line and are therefore unacceptable. If the mine adopts a real-time monitoring and warning system to give advance warning of a potential strainburst as shown in the Fault Tree diagram in Figure 5 in Chapter 5, the risk of a strainburst drops from 60.9% to 12.2%. This reduces the probability of all the outcomes, bringing them well below the intolerable risk limit, as shown in Figure 17.

### 7.3 Real-time risk monitoring using a Bayesian network

Once the risk thresholds for the mine are defined, the risk levels can be monitored to plan and adjust the mitigation measures to keep the risks at affordable levels. Periodic inspections of influencing factors enable the reassessment of risks. However, it is possible to miss risk escalation if it happens in the intervals between periodic inspections. Real-time risk monitoring can help overcome this problem. Data from on-site instrumentation can be combined with inspection-based parameters and expert opinions using a Bayesian network to carry out real-time risk monitoring (Publication 5). Figure 18 shows the real-time risk monitoring process using a BN.
The first step of the process is to define the failure mechanism of the risk in question using Bayesian network nodes and the relationship between the nodes. These nodes can be numeric nodes with numerical values such as uniaxial compressive strength, joint set numbers, roof deformation in mm, etc. Alternatively, these nodes can be non-numeric, with subjective states such as ‘high’, ‘medium’, ‘low’, etc. (Fenton et al., 2007). If the nodes are non-numeric, the prior probability of each of the nodes will have to be defined. Numeric nodes can consist of information which is collected in real time, such as roof deformation measurement using an extensometer, seismicity using geophones, etc. For these nodes, appropriate site-wide instrumentation needs to be planned so that sufficient data is collected and their prior probabilities are defined using probability distribution. Numeric nodes can also consist of data that is collected intermittently through inspection and is not continuous. Joint set numbers, joint roughness, blast vibrations, etc. fall under non-continuous numeric nodes. Either these nodes can be defined using a probability distribution or the distribution can be learnt using parameter learning. After the nodes and their prior probabilities are defined, the BN is solved for the current risk level on the basis of the available information. As data is fed from real-time instrumentation, the risks are updated in real time to inform the relevant stakeholders. The same network can also be used to feed information on incidents and near-misses that happen in the mine to carry out backward inferencing and revise all prior probabilities. This method also helps the incident investigation to arrive at the most likely cause of the incident and improve the accuracy of the forecasting model.
In this thesis, advances are shown in the fields of preparing for and carrying out geotechnical risk assessment in underground mines through preliminary risk classification, detailed geotechnical risk assessment scope preparation, the selection of an appropriate risk assessment methodology, the evaluation of likelihood and consequences using Fault Tree and Event Tree Analysis, risk assessment for spalling and stope collapse using Bayesian networks, and parameter learning for a roof collapse using Bayesian networks. Each of these research topics represents a summary of trailed work and current research: GRA scope preparation and method selection were trailed in the Pyhasalmi mine, while the Bayesian network-based risk assessment concept is being tested in the Kemi mine.

The preliminary geotechnical risk classification using geotechnical hazard potential rankings was designed to kick-start the risk management process from stages as early as pre-feasibility studies. It can be used to formally justify a detailed risk assessment. The guideline, however, does not provide an exhaustive list of geotechnical parameters which applies to all underground mines. The thresholds of geotechnical parameters recommended for different mining stages is established on the basis of a literature review and subjective opinion. These thresholds need to be validated in a mine for the suitability of the recommended geotechnical parameters for risk classification and their threshold values. For instance, Roof Fall Risk Index (RFRI) data, if available, can replace the Mathews Stability number for preliminary risk assessment in a coal mine if RFRI values are more readily available. The use of the alphabetic ranking system is encouraged in mining areas to make the workers aware of the general risk in the area so that they can be more vigilant. The Geotechnical Hazard Potential table is also meant to be used as a guideline for potential consequences. The GHP table should be revised on the basis of site observations to best reflect local geotechnical conditions.

Outlining the scope of a risk assessment when carried out for a specific hazard or general site was found to be the most ambiguous task in this research. Given the multi-disciplinary composition of the risk assessment team, it was often noticed that several potential causes were assigned to a hazard with vague likelihood values. The time spent on preparing a document outlining the scope of a geotechnical risk assessment can thus help resolve this issue and enable a timely completion of the risk assessment. Although the GRA has been broken down into its sub-elements, the list is not exhaustive and should be
revised on the basis of local expertise. The recommendation of hazard identification tools and risk assessment parameters is recommended through a literature review based on their usage in the past. A mine, however, can select its own method for hazard identification based on the local expertise available. Combinations of methods can be used to carry out hazard identification as well. During the research, it was discovered that mines seldom had a detailed database of incident investigations identifying potential causes and their frequencies. Incident investigations were limited to major accidents which resulted in production loss or injury. In order to validate the causes of incidents, it is advised to carry out preliminary investigations of minor incidents and near misses and document the findings. In all cases of preliminary risk classification, defining the geotechnical hazard potential, and the selection of risk assessment approach for GRA, the recommendations can be revised using a Bayesian network-based parameter learning process as described in this thesis.

A lack of historical data, detailed geotechnical information, and incident investigation makes probabilistic risk assessment suitable in mines. A probabilistic risk assessment can work with subjective opinions to complete a risk assessment in the absence of data. Fault Tree Analysis enables the breaking down of hazards into their root causes and the assigning of likelihood to the root causes to be combined in order to make a final likelihood estimation of an incident. Fault trees, however, can only work with Boolean values of “True” and “False” for each root cause. For instance, a fault tree node of groundwater contributing to a roof collapse can only be evaluated for the presence and absence of groundwater in a fault tree and not for the various quantities in which the groundwater can be present. Additionally, fault trees solve probability values by assuming conditional independence between the contributing factors. Similar restrictions are faced when using event trees for consequence analysis as they also only work with Boolean nodes and conditional independence. Modelling a complex failure with several interdependent factors can therefore be difficult with Fault Tree and Event Tree Analysis (FTA – ETA). They do, however, provide a simple quantitative risk assessment tool that can be readily used at a mine site without the need for extensive computational power. They also provide a good visual representation of how a failure propagates.

Bayesian network-based (BN) risk assessment can overcome the limitations of conditional independence and the complex causal relationship between hazards and their causes. The ability to work with expert opinions in the form of prior probabilities also means that it can be used at a mine site with no prior risk assessment or incident investigation history. The use of conditional probability tables and nodes enables the modelling of incident causation where the causes are interdependent. The ability to work with non-Boolean values and continuous variables reduces the number of nodes needed to model the hazard. The use of continuous variables in the risk assessment also enables the use of instrumentation data such as extensometers, seismic monitoring, and groundwater flow in real time to carry out real-time risk assessment. The probability values assigned to the nodes do not need to be absolute and proba-
bility distributions can be used instead. The challenge of defining a prior probability in the BN can be overcome with the use of parameter learning. Parameter learning using a Bayesian network provides the framework of learning from history to update the risk forecast. While Bayesian network-based risk assessment offers benefits, its reliance on prior probabilities is also one of its key weaknesses. Incorrect prior probabilities will produce incorrect risk forecasts and this is only corrected through the investigation of every subsequent incident. Error in modelling the causation of the incident will also produce incorrect forecasts. Given the reliance on expert opinions in the absence of data, human error overall plays a key role in the effectiveness of the risk model. These errors can take the form of several biases that an expert may have when modelling the risk. The use of continuous variables also requires the use of proprietary software and the expertise to use it, unlike Fault Tree and Event Tree, which use simple probability calculations to forecast risk. Additionally, Bayesian network-based risk assessment requires introductory training in Bayes’ theorem and Bayesian networks to create a causal model that may not be readily available at a mine site. Despite the shortcomings, the ability to work in the absence of data, the ability to improve the forecast with additional data, and the ability to assist in incident investigation following an accident make a Bayesian network a good candidate for risk assessment in mines.

Each of the areas researched here has potential for future research. The preliminary risk classification can be made specific to different types of mining. The classification can also be made specific to different rock types, such as coal mining, mining in brittle rock, etc. The guidelines developed to define the scope of risk assessment need to be trialled in underground mines to evaluate their suitability. A Bayesian network-based risk assessment can be expanded to include human error and expert bias. It can incorporate real-time data from on-site instrumentation to carry out a real-time risk assessment.
9. Conclusions

The main conclusions of the research address the methodology used to carry out a detailed geotechnical risk assessment in underground mines. Underground mines or a section of a mine can be pre-classified for hazards using Geotechnical Hazard Potential (GHP) rankings. Detailed guidelines were developed to prepare for a geotechnical risk assessment and selection criteria for choosing an appropriate hazard identification tool and risk assessment parameters were defined. The use of Fault Tree and Event Tree Analysis was demonstrated to identify the root causes behind a stope collapse and the potential consequences arising from a stope collapse. Finally, the use of Bayesian networks to make an expert opinion-based risk assessment, data-driven risk assessment, and a hybrid risk assessment combining data and expert opinions was demonstrated. The detailed conclusions are listed below.

1. A geotechnical risk classification system for mining is created which can be used from the early stages of mine planning through to mining operations.
2. A selection criterion to choose a suitable risk assessment approach using a numerical ranking system is proposed.
3. It is suggested that Bayesian networks have advantages over Fault Tree and Event Tree Analysis to assess geotechnical risks in mining.
4. Stope collapse forecasting using a Bayesian network is shown by using interview data from experts in an underground mine.
5. Learning from historical roof fall frequencies through parameter learning with Bayesian networks is shown to further improve the capabilities to forecast future incidents.
6. Annual roof fall estimates using Poisson distribution show identical results when either frequentist or Bayesian estimation is used in the case studied.
7. The results from the Bayesian network show that the observed data from the cases that were studied has a 70% likelihood of being observed under normal distribution and a 30% likelihood of being observed under Poisson distribution.
8. A new method to combine multiple probability distributions to forecast the geotechnical risk is proposed.
9. Real-time geotechnical risk assessment using a Bayesian network is proposed by the use of instrumentation data from a site.
It can be concluded that all six objectives set for this thesis were achieved: a preliminary risk classification system was defined, guidelines to define the scope of a formal geotechnical risk assessment were developed, a selection criterion to choose a suitable risk assessment approach using a numerical ranking system was developed, a Bayesian network-based risk assessment that works with expert opinions was developed, parameter learning using a Bayesian network to learn from historical data which can be used to forecast future incidents was shown, and finally, the use of Bayesian networks to carry out a real-time geotechnical risk assessment and the use of a modified FN diagram for risk representation was described. On the basis of the results, the following future work is recommended:

2. Trial of the numerical ranking system for risk assessment parameter selection in an underground mine.
4. Parameter learning of all the root causes of a fault tree and event tree using Bayesian networks.
5. Calibrating the expert opinion-based risk assessment model in an underground mine.
6. Testing the real-time risk management framework using instrumentation data.
7. Defining guidelines to choose risk mitigation measures on the basis of risk levels and testing the effectiveness of the mitigation measures.
References

Agena 2017. AgenaRisk: Bayesian network and simulation software for risk analysis and decision support. 7 ed.


References


Underground mining involves operating under geotechnical uncertainties. Geotechnical incidents arising from it can cause catastrophic damages in terms of injuries and financial losses. Detailed geotechnical risk assessment can help forecast an impending hazard and put mitigation measures in place in advance to prevent it. Accurate risk assessment however, requires extensive geotechnical data and detailed incident investigation record, which is often missing in mines. This thesis explains, how to carry out risk assessment in real time with abundant, moderate or no historical data.