Dealing with uncertainty and risk in rock engineering design

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ABSTRACT: A method for risk-based design is described in this paper. Probabilistic methods of analysis are applied to stress modelling to determine the probability of exceeding a given depth of failure. Suggestions are provided for dealing with geotechnical uncertainty. The understanding of aleatory variability can be improved by collecting more data and improving the quality of data through training and quality control. Stress and model uncertainty remains a challenge in geotechnical engineering. Some degree of subjective engineering judgment will therefore always be required in geotechnical design.

Acceptance criteria then need to be defined in terms of safety and economic risk. Corporate risk matrices can be used for assessing the risk in terms of the probability and consequence. International safety benchmarking and safety milestones should be considered. The cost of rehabilitation of tunnels and the financial losses due to lost production are assessed using the model. A typical risk matrix is used to evaluate the level of risk. Different types of excavations have different risk profiles based on the potential impact on production.

1 INTRODUCTION

By its nature, rock engineering is subject to a great deal of uncertainty and variability (Hadjigeorgiou and Harrison, 2011; Brown, 2012; Contreras and Ruest, 2016), which need to be taken into account in the design process and in the management of rock-related risks.

Variability is a property of nature and is a measure of the change in rock mass characteristics over time and space. The variability can be described with statistics and the probabilities related to variability can be interpreted as a frequency of occurrence. Uncertainty is a state of mind and is a product of our lack of knowledge, which can be reduced with more measurement and improved understanding. Probabilities related to uncertainty are best interpreted as a degreeofbelief. Uncertainties include measurement errors, insufficient data, sampling bias, stress state uncertainty, and model uncertainty. The understanding of variability can be improved by collecting more data and improving the quality of data through training and quality control. Stress and model uncertainty remain a challenge in rock engineering. Some degree of subjective engineering judgement will therefore always be required in geotechnical design.

The philosophy provided by (Vick, 2002) distinguishes between a 'relative frequency approach' and a "subjective, degree of belief approach" is useful:

Relative frequency approach: The probability of an uncertain event is its relative frequency of occurrence in repeated trials or experimental sampling of the outcome.

Subjective, degree of belief approach: The probability of an uncertain event is the quantified measure of one's belief or confidence in the outcome, according to their state of knowledge at the time it is assessed.

Vick (2002) argues that both these interpretations of probabilities are equally valid and that one cannot afford to ignore either interpretation in geotechnical engineering. Baecher & Christian (2003) note that the frequency and belief co-exist in our modelling endeavours and that calculated probabilities in geomechanics are generally not the one or the other, but a mixture of both.

Deterministic methods have been applied in rock engineering and designs are usually evaluated by determining a safety factor. Often, mean values are used for the rock mass input parameters. A safety factor (SF) of 1.5 or 2.0 usually caters for the inherent uncertainty and variability. However, if the uncertainty and variability are high then the design may not be adequate. Conversely, the design may be overly conservative and expensive if the variability is low. It is therefore important to consider uncertainty and variability and to apply them in design.

Many powerful methods for evaluating uncertainty and probabilistic analysis of geotechnical stability have been developed over the years (Rosenblueth 1975, 1981, Harr 1996, Baecher & Christian 2003, Bradley 2007, Brown 2012, Kroese & Rubinstein 2012, Contreras & Ruest 2016). These methods of analysis have been applied to the design of rock slopes (Terbrugge et al. 2006, Tapia et al. 2007, Steffen et al. 2008, Wesseloo & Read 2009, Chiwaye & Stacey 2010, & Contreras 2015), pillars, stope spans, access development, support, and other aspects of rock engineering (Joughin, Swart & Wesseloo 2000, Valley, Kaiser & Duff 2010, Lü & Low 2011a, b, Joughin et al. 2012a, 2016, Lü, Chan & Low 2012, Abdellah, Mitri & Thibodeau 2014, Langford & Diederichs 2015).

Despite this, these methods are not widely applied in underground mining geotechnical design and deterministic methods are generally preferred. This is partly due to the additional effort required for probabilistic analyses and a lack of tools to make such analysis easily achievable on a mine site. Another stumbling block seems to be the lack of prescribed 'acceptable probabilities of failure (PF)' which serves as design acceptance criteria.

Universal acceptance criteria are not useful because the probability of failure, on its own, has little meaning within the mining context as the important factor that needs to be managed is not failure, but risk. In mining, failure with limited adverse consequence is preferable to unnecessary stability at a high cost. Hence, a risk-based design approach needs to be applied, where the acceptance criteria are defined in terms of risk and therefore include probabilistic assessment and risk evaluation components. The risk evaluation process therefore requires some practical understanding of the potential consequences.

The potential risk of injuries and fatalities can be determined by developing an exposure model, which considers the temporal and spatial coincidence of personnel with an incident such as a rockfall or a rockburst. Economic consequence models can also be developed to evaluate the potential losses due to production disruptions, rehabilitation of damaged excavations, or repairs to damaged equipment. Practical mitigation measures can be implemented to further reduce the risk, and these models can be used to evaluate the residual risk.

Acceptance criteria then need to be defined in terms of safety and economic risk. Corporate risk matrices can be used for assessing the risk in terms of the probability and consequence. International safety benchmarking and safety milestones should be considered. Much of this work was previously published in (Joughin 2017) and will be published in greater detail in three book chapters later this year (Joughin et al. 2018, Wesseloo & Joughin 2018 as well as Wesseloo & Muaka 2018).

1.1 Input data

Rock mass characteristics and intact rock strength properties should be collected for the probabilistic analyses. Increasing the amount and quality of data will improve the confidence in the understanding of the natural variability. It is important to note that this usually increases the variability, as the sample size becomes more representative of the entire population. As a result, there is often a tendency to underestimate the natural variability, when there is limited data and it may then be necessary to increase the variability using experience and judgement. Confidence intervals of the observed mean (typically 95%) provide an estimate of the range of the true population mean. The use of confidence intervals to validate the data sets has been discussed by various authors (Baecher & Christian 2003; Hadjigeorgiou & Harrison 2011 as well as; Contreras & Ruest 2016). Unconventional methods, such as Bayesian statistics may provide a better way of quantifying uncertainty (Brown 2012, Contreras & Ruest 2016, but applications are still being developed in geotechnical engineering and tools are not yet readily available. Experience and engineering judgement are essential.

Probability density functions provide useful representations of data for probabilistic analyses. Some examples are briefly provided here, which are explained in more detail in Joughin et al (2018).

Rock mass characterisation data estimated from core logging, should be composited over regular, discrete intervals representative of the problem dimension (figure 1). This is necessary to build a probabilistic model of the data that captures the variance at the scale of the problem. Probability density functions can then be fitted to the frequency distribution of the data set.

Intact rock strength data can be represented using the Hoek-Brown strength envelope (Hoek et al.2002), as illustrated in Figure 2. Assuming a constant mi allows one to calculate the equivalent UCS value for each of the data points and obtain a distribution capturing the variance of the strength envelope.

Geometric effects, such as overbreak (as a result of poor blasting) can also be represented in the analyses. Underground measurements should ideally be used to determine the variability of excavation or pillar dimensions, but in the absence of actual data, a reasonable assumption capturing the level of uncertainty associated with this parameter is necessary. Simple triangular or uniform distributions are often appropriate in these circumstances.



Figure 1. Determining the variability of rock mass characterisation data



Figure 2. Determining the variability of intact rock strength

Stress uncertainty can have a significant influence on the results of the analyses. Often stress data is limited or not available. Errors are also common in the available stress measurements and it is often not easy to determine whether variability is representative or due to errors. Generally, the magnitude of the vertical stress can be estimated with some degree of confidence, but a greater degree of uncertainty is associated with the maximum and minimum horizontal stresses. Principal stress orientations are often not known with certainty. Figure 3 shows an example distribution of the magnitude and orientation of the stress field.



Figure 3. Distribution of stress input parameters a) field stress magnitude b) field stress orientation

1.2 Probabilistic analyses

In probabilistic analyses, the Monte-Carlo (MC) ap-proach described in Kroese & Rubinstein 2012 is the best known and most widely used, often being applied to simple analytical closed form solutions. However, numerical modelling, particularly elastoplastic methods, require long solution times and it is generally not practical to run many models and therefore alternate methods are more typically used. Three methods, namely the Point Estimate Method (PEM) (Rosenblueth 1975, 1981, Harr 1996, Chris-tian & Baecher 1999, 2002, Valley, Kaiser & Duff 2010), response surface method (RSM) (Bradley 2007, Lü & Low 2011b, Langford & Diederichs 2015) and the response influence factor (RIF)(Tapia et al. 2007, Steffen et al. 2008, Wesseloo & Read 2009, Chiwaye & Stacey 2010, Joughin et al. 2016) are more often used to perform probabilistic anal-yses, where computational efficiency is critical. A comprehensive explanation of these methods will be provided in (Wesseloo & Muaka, 2018).

An efficient probabilistic analysis approach, which utilises elastic modelling and the principle of superposition of load effects has been developed and implemented into an app (Wesseloo 2016) in mXrap (Harris & Wesseloo 2015). It is considered that the loads and their resulting effects can be add-ed or subtracted providing that the structure behaves as a linear elastic material. Unit stress analyses are conducted for each component of the stress tensor. Figure 4 shows probability of failure contours calcu-lated using this method (Joughin et al. 2016, Joughin 2017). These results can be used to determine the probability of exceeding a given depth of failure.

Although the use of elastic superposition provides a lot of insight into the problem and the influence of uncertainty, in many cases the use of elasto plastic analysis may be required. In such cases the method of elastic superposition can be used to perform a parameter reduction study. This may be very important since the reduction of parameters included in the use of the PEM, RIF and RSM will reduce the number of numerical analyses necessary for the probabilistic evaluation.

Probabilistic block stability analyses can be performed using JBlock (Esterhuizen 2003) originally applied in a risk-based design method for support design in South African narrow tabular stopes (Joughin et al. 2012a, 2012b). JBlock is designed to create and analyse geometric blocks or wedges, based on collected data in the form of joint orienta-tions, trace lengths, joint conditions and friction an-gles. The blocks are formed by the intersection of joints or faults in the excavation roof, which can fail by sliding or falling into the excavation (Figure 5). JBlock is still limited in its ability to handle 3D tun-nel geometries. An example of its use in tunnels is provided in (Joughin et al. 2016), which also serves to illustrate that absolute accuracy and the most so-phisticated analysis is not a prerequisite for a robust risk based design.

Currently discrete fracture network modelling and the subsequent is rarely used in design of mining drifts (Grenon et al. 2017). In recent years great advances in discrete fracture networks modelling and block stability analysis have been made and probabilistic evaluation of structurally controlled instability will become more advanced and easier and to perform(Grenon et al. 2015, 2017).

Detailed examples of these methods of analysis will be provided in(Joughin et al. 2018).



Figure 4. Efficient calculation of the probability of failure using elastic superposition and Monte-Carlo simulation in mXrap



Figure 5. Rockfall simulation in JBlock

1.3 Risk evaluation models

Risk evaluation models should be developed to quantify the consequences of stress damage or rockfalls. This requires a practical assessment of mining layouts, potential zones of damage/rockfalls, production schedules and exposure of personnel, taking previous experience and judgement into consideration. The purpose of the model is to realistically estimate the cost of damage, loss of revenue and the potential for injuries. It should not be overly complex, but should address the most important consequences. A risk evaluation model is briefly described below, while Joughin (2017), Joughin et al. (2018) provide a more detailed discussion.

The cost of damage, loss in revenue and potential for injuries are all a function of the length of the tunnel affected. It is therefore important to estimate the expected frequency of occurrence and extent of damaging events in a tunnel. Depending on the function of the tunnel, the effect on production and exposure of personnel will vary. All these factors need to be taken into consideration.

1.4 Frequency and extent of damage

For rockfalls in a tunnel, the probabilistic block stability analysis results in a distribution of rockfall area and volume for the specified support system in a geotechnical domain. Since the simulation area (tunnel roof area exposed), it is easy to normalise by the total tunnel length exposed and duration of mining to determine annual cumulative probability distributions (Figure 6). For the purposes of the model it was assumed that the rockfalls will be distributed evenly over the length of tunnel and the duration of the mining.



Figure 6. Cumulative normalised (years) rockfall area probability distribution

In the case of a tunnel subjected to high stress, it is necessary to estimate the frequency of occurrence of damage affecting a given length of the tunnel (Figure 7). Critical levels of damage can be selected using subjective engineering judgement based on the depth of failure or deformation in the tunnel walls. The maximum deformation that can be tolerated before the tunnel becomes unserviceable or unsafe is a suitable criterion.

The total length (L) of the access ramp, sublevel drive or stope drives will not normally be affected at the same time. In practice, the potential damage affected length (l_p) at a given time will be a function of the mining layout and sequence and the resulting stress influence. In the case of stope drives, the greatest stress change is experienced close to the stope abutment and this is when large deformations are most likely to occur. The probabilistic stress analyses can be used as a guide to determining l_p . For the sublevel drives, the greatest stress change will occur as a stope reaches its limit. The access drive will experience less significant stress changes, since it is further away and while the probability of exceeding deformation criteria is expected to be lower, the potentially affected length may be larger. Selecting an appropriate l_p will always be subjective, particularly in the case of the access ramp, and it is therefore necessary to test different l_p values and assess the influence on the model.

This l_p can be further sub-divided into short tunnel segment lengths (l_s), which represent the natural variability in rock mass characteristics and ideally references to the composite interval length used for determining the variability of the rock mass characteristics (Figure 1).



Figure 7. Potential damage zones

The probability (p) of exceeding the deformation criteria, determined during the probabilistic analysis of stress damage, is therefore applicable to the segment length. When the l_p is affected, some or all of the length may experience excessive deformation. Figure. 8 shows some scenarios of possible damage over l_p for a given p.



Figure. 8. Possible damage over the potentially affected length of a tunnel

The probability $P_d(k,n,p)$ of exactly k segments being excessively damaged can be estimated using the binominal distribution:

For the purposes of the model, it was assumed that damage would occur over the duration of mining and the entire length of the tunnels would ultimately become exposed to stress damage. The resulting cumulative normalised expected frequency distribution for the main ramp is shown in Figure 9. Sub level drives and stope drives will have very different stress damage hazard profiles and need to be analysed separately.



Figure 9. Cumulative normalised (years) expected frequency damage length distribution for the access ramp

1.5 Economic losses

The estimation of losses associated with rock damage in underground mines has been addressed by a severalauthors (Joughin et al. 2012a, 2016, Abdellah, Mitri & Thibodeau 2014). The most significant economic consequences of the damage are the cost of remediation of the damaged section of the tunnel and the lost production due to inaccessibility during rehabilitation.

Rehabilitation usually involves the removal of loose rock and damaged support and then re-supporting. The cost of rehabilitation is the product of the length of damage and the cost per unit length. The duration of rehabilitation will affect the production loss and can be estimated as the product of the length of damage and rate of rehabilitation. For rockfalls it can be assumed that the damaged length is the rockfall area divided by tunnel width. Alternatively, the rockfall volume may be considered a more suitable parameter for estimating the cost and rate of rehabilitation, based on experience.

During rehabilitation, production is likely to be affected, but this depends on the purpose of the tunnel.

Using Figure 7, it is shown that rehabilitation in the main access ramp would always affect the full production from these stopes and this will have an immediate effect. Rehabilitation of the sublevel drive would probably only effect half of the production and there may be some flexibility in the production schedule that allows some time before production is affected. The proportion of daily production influenced when a stope drive is being rehabilitated depends on the number of active stopes in production and there is invariably some flexibility, so the production impact is not immediate. A simple algorithm can be used to estimate the potential revenue loss per damaging incident as a function of duration of rehabilitation (a function of length of damage), revenue per ton mined and amount of production affected per day.

The total damage loss per incident is therefore the sum of the revenue loss and rehabilitation cost. Algorithms can be developed in a similar manner to account for other potential damage losses.

The cumulative frequency distributions in Figure 6 and Figure 9 can be presented in terms of damage loss.

1.6 Safety

Individual safety risk is concerned with the risk to any particular individual and one would focus on assessing the risk to individuals at highest risk. The exposure of personnel to rockfalls is primarily a function of temporal and spatial coincidence or being in the wrong place at the wrong time.

Temporal coincidence is taken as the proportion of time people are exposed to a hazard. As different shifts may have different exposure times it is best to evaluate this on a shift basis.

The spatial coincidence depends on the length of tunnel that is excessively damaged (Figure 9) and therefore exposure needs to be calculate for any possible damage length l_d that could occur ranging between l_s and l_p (the total potentially effected length). If a good support system is applied and conservative serviceability criteria are effectively implemented, it is likely that the support will be replaced before rockfalls occur. An additional factor can then be applied to represent this risk mitigation measure.

For block failures an equivalent length of damage can be determined by dividing the rockfall area by the width of the tunnel. Spatial coincidence can be expressed as the length of damage (ld) divided by the length of exposure (ld) (Figure 10).



Figure 10. Spatial Coincidence

Exposure can be mitigated by protecting personnel in the canopy of a vehicle (vulnerability) and by monitoring the deformation and removing personnel, when the deformation criteria is exceeded.

The individual exposure can by determined by considering the temporal and spatial coincidence for a single person, vulnerability, monitoring and then adjusted for the number of shifts worked per annum. Personnel may be exposed to a range of possible rockfalls represent by the cumulative expected frequency distribution (Figure 6 and Figure 9) and therefore the probability of injury is the sum of the product of individual exposure per rockfall size and frequency of occurrence.

2 ACCEPTANCE CRITERIA

Figure 11 illustrates the relationship between factor of safety (FS), probability of failure (PF) and Risk as design acceptance criteria within the design process. Due to the simplicity and general accepted nature of FS design, the FS assessment is seen as the first step in performing any engineering design. Based on very low values of FS, one my deem the design unacceptable and improve on the design, or in cases where other considerations dictate the design, a very high FS may be sufficient to accept the design. In some circumstances, especially in cases where potential for optimisation exist the reliability of the design need to be quantified. Similar to FS, a low or high PF may be sufficient to deem the associated risk inconsequential or unacceptably high.

Societal safety risk is concerned with risk to all employees collectively. It is important to consider all personnel that could be exposed to rockfalls. Under different circumstances there could be individuals or groups of people working or travelling through the length of exposure (l_e). It is important to analyse different exposure groups.

In the case of groups of personnel working or traveling together, the probability of injury of entire the group can be calculated as for an individual

The binomial distribution can be used to calculate the probability of one or more people being injured when they are randomly travelling through a tunnel, because this takes the random coincidence of more than one person into consideration.

Decision making based on FS or PF is often limited to the geotechnical team. The geotechnical team then implicitly accepts a risk profile without quantification. For some designs in the mine, this may *not* be acceptable and the risk associated with a design should be quantified. In such cases the design acceptance criteria should be dictated by management through the company risk profile.

The risk assessment provides a context as well as an accepted risk level to which the engineer needs to design.

Acceptance criteria will be published in (Wesseloo & Joughin, 2018) and are summarised briefly herein.

2.1 Economic acceptance criteria

The economic risk as a design acceptance criteria aims at maximising shareholder value. The term "maximising shareholder value" does not imply maximising the planned return. The difference lies in the risk associated with different options. A very risky venture with a high possible return may have low shareholder value as the probability of realising that return on the investment is very low. The economic risk profile of a mine is defined by management who is accountable to the shareholders.

It ultimately boils down to the risk-reward balance and the risk profile of the company and, the risk-reward balance best applicable to each situation. The rock engineer is seldom, if ever, in the position to define the risk profile of the company. This should be the task of management. Without guidance from management as to the appropriate risk level, the engineer cannot design appropriately (see

Figure 11).

Manymining companies utilise risk matrices, such as Figure 12, to define acceptance criteria for risk assessments, which usually involves a great deal of engineering judgement and estimation. The likelihood of an event occurring (rare to certain) and the severity of the consequences (insignificant to catastrophic) form the rows and columns of the matrix and the intersections determine level of risk (low to extreme).



Figure 11. Relationship between FS, PF and Risk as design acceptance criterion within the design process

While the category names for the levels of likelihood, severity and risk are fairly universal, the boundaries of these categories do vary significantly. The scales are usually qualitative or semi-quantitative and are often updated with time (Brown 2012). Economic risk tolerances may vary depending on the size of the operation. Likelihood categories can be described in terms of probabilities, time periods or simply qualitative descriptions. Applying different likelihood boundaries will influence the interpretation of levels of risk. Some authors have suggested using risk matrices for risk evaluation (Brown 2012, Abdellah, Mitri & Thibodeau 2014, Contreras 2015, Joughin et al. 2016), but the subjective nature of these risk matrices can lead to different interpretations.

The risk matrix in Figure 12 has time intervals to define the boundaries of likelihood categories. This enables a more practical interpretation of likelihood and a common understanding of decision-making can be achieved.

Using the cumulative normalised expected frequency damage length distributions of and the economic model, cumulative normalised expected frequency distributions of economic loss can be presented using a risk matrix. The risk profile, based on stress damage for the access ramp is presented in Figure 13. The risk profiles for different excavations will differ considerably. Both the severity and frequency of occurrence of occurrence will differ.

The probability acceptance level (p) for design should be selected to ensure that the risk is medium. Based on the risk profile presented, the p values for designshould be 2% for access drives.

2.2 Safety Acceptance criteria

Safety Risk as a design criterion has been socially difficult to deal with. Some company policies prevent the use of the words "probability of fatality". Preventing the use of the words does nothing to reduce the risk to personnel and, in fact may result in inadequate attention given to the issue.

A widespread safety objective of the mining industry can be summed up in the slogan "zero harm". This is a praiseworthy goal and the only morally defensible stance. It should, however, not be mistaken for a design acceptance level. The engineer *cannot* design for a zero probability of injury (in the absolute sense).

Likelihood	Severity of consequences				
	Insignificant > \$1,000	Minor > \$10,000	Moderate > \$100,000	Major > \$1,000,000	Catastrophic > \$10,000,000
Daily to	High	High	Extreme	Extreme	Extreme
> Monthly	Medium	High	High	Extreme	Extreme
> Annually	Low	Medium	High	Extreme	Extreme
> 1 in 10	Low	Low	Medium	High	Extreme
Rare	Low	Low	Medium	Medium	High

Figure 12. Risk matrix example



Figure 13. Economic risk profile for the access ramp (stress damage)

With respect to safety risk, management is accountable to the shareholders as well as to society through adherence to guidelines prescribed by regulatory bodies. Accepted risk levels, therefore, do not have anything to do with any individual's appetite for risk but is a measure of what society accepts as reasonable. Ideally guidelines on what risk levels are accepted by a society needs to be developed through political process. However, in mining, such guidelines do not exist and the engineers are forced to borrow risk acceptance levels from elsewhere.

Guidance on what risk level is accepted by society can be obtained by comparing guidelines provided by government agencies and regulatory bodies of different countries and industries, mainly industries dealing with risks to public safety.

Many different regulation agencies of many different countries have provided guidelines. These include British Columbia Hydro and Power Authority, the Australian National Committee on Large Dams ANCOLD, Australian Geomechanics society, subcommittee on landslide Risk Management (2000), US Department of Interior Bureau of Reclamation, US Nuclear regulatory Commission, US federal Energy regulatory Commission, Norwegian petroleum industry, Hong Kong Planning Department, Technical Advisory Committee on Water Defences of the Netherlands, Britton's Health and Safety Executive, (2001, 1992, 1989). Many of the guidelines employ the ALARP or ALARA concept which is the acronym for 'As low as reasonably possible' or 'attainable'. Very high risk are deemed "unacceptable" while very low risks are deemed "acceptable" with the ALARP region

between these two defining the situation where further risk reductions is impractical or the cost are grossly disproportionate to the improvements made.

For design purposes one need to know what risk level defines the ALARP region.

Accident statistics provide a context to what risk levels the public are exposed to daily. One needs to assume involuntary risk for the mining work force unless it can be shown that the individual was empowered (and cognitively able) to consciously accept the risk in exchange for a perceived reward. A risk acceptance level for individual safety risk of 10^{-5} to 10^{-6} seems to be an appropriate and defensible design value in line with societal expectations.

In addition to the risk to an individual, the risk to society needs to be evaluated. The exposure of the public to a mining structures comes mainly from the devastation caused by tailings dam failure. For the mining, the public is not at risk and we will only concentrate on the societal risk to the work force.

Societal safety risk acceptance levels are often presented in what is referred to as F-N charts (Figure 14). The F-N chart is in principle an inverse cumulative probability distribution on double logarithmic scale. The yearly probability of N or more fatalities on the vertical axis plotted against the number of fatalities N. The upper and lower boundaries of the ALARP region in (Figure 14) were determined for the Australian mining industry and a 500 m long tunnel, using the Hong Kong Planning Department criterion. These are, to some extent, dependant on the scale of the analysis and should be adjusted according to the length of the tunnel. This will be explained in more detail in(Wesseloo & Joughin, 2018).



Figure 14. Safety risk acceptance levels derived for Australian mining industry based on a National Risk Acceptance leveland the Hong Kong Planning Department criterion.





The fatal incident risk profile for the access ramp is presented in Figure 15 which is the result of the safety risk evaluation model. The shape of societal risk curves for the access ramp is a function of the binomial distribution. The societal risk curves in mechanised mines have very steep profiles, because larger groups of personnel are not often exposed. Individual risk is represented on the graph as individual points on the vertical axis. Decisions in mechanised mines are usually governed by the risk of incidents with one or two people and by the individual risk, rather than major catastrophic events, where large numbers of people are fatally injured.

For safety in the access ramp, the design probability criterion could be as high as 10%, but this would be unacceptable from an economic perspective. However, for the other situations, this is quite different. In stope drives, the economic consequences are low, but personnel are exposed for longer times and the individual risk, becomes the defining risk criterion.

3 CONCLUDING REMARKS

The risk-based design process is applicable under high stress conditions, it takes into account geotechnical uncertainty. The understanding of variability can be improved by collecting more data and improving the quality of data through training and quality control. Stress and model uncertainty remain a challenge in geotechnical engineering. Some degree of subjective engineering judgement will therefore always be required in geotechnical design.

When determining 'acceptable probabilities of failure' for design it is necessary to evaluate the risk. The potential financial losses associated with stress damage will differ for different types of excavation. An economic model is a useful tool for risk evaluation. Risk matrices used on mining operations assist with the practical interpretation of risk.

Safety acceptance criteria should be defined based on international benchmarking and societal norms.

The relative frequency approach is used by the insurance industry, where large amounts of data are available and it is possible to assess the potential risk quite reliably. In geotechnical engineering, it is appropriate to incorporate a subjective degree of belief approach. Where good data is available, this will improve confidence in the outcome and the degree of belief, but the interpretation will remain subjective.

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