Mining Geomechanical Risk 2019 – J Wesseloo (ed.)

doi:10.36487/ACG_rep/1905_02_Mishra

Combining expert opinion and instrumentation data using Bayesian networks to carry out stope collapse risk assessment

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Abstract

Stope collapse is a common form of accident resulting in property loss and bodily harm in mines. There are several methods to carry out risk assessment for stope collapse incident in an underground mine. This paper presents an alternate method to determine stope collapse probability using Bayesian belief networks. The alternate methodology is designed to replace a subjective risk assessment process in a metal mine in Finland. First, the stope collapse failure mechanism specific to the underground mine was established by carrying out interviews with stake holders in the underground mine. These failure modes have been mapped using Bayesian network with the use of expert opinion. The expert opinions were obtained from the interviews and their correlation and interdependencies have been defined. Use of continuous data obtained from site instrumentation in the Bayesian network has been discussed to validate the expert opinion model and to create a near real-time risk monitoring system. Updating of failure probabilities using new evidence has been discussed using a 'what-if' scenario analysis and use of backward inference to carry out incident investigation in the event of a failure has been described. The paper further elaborates on how Bayesian modelling for risk assessment can be incorporated in mining to justify mitigation measures and use this as a decision-making tool. When combined with existing data collection systems in the mine, this can form the backbone for a real-time risk management system.

Keywords: *Bayesian network, expert opinion, interview, stope design, mitigation*

1 Introduction

Stope collapse is one of the common forms of accident resulting in property loss and bodily harm in mines. The On-Line Risk Management in Deep Mines (ORMID) research project aims to understand rock failure process surrounding mine openings over time and to apply this knowledge to mitigate geotechnical risks through geotechnical risk assessment. For the site of research, a Finnish metal mine, which uses sub-level stoping as the mining method, was selected. Risks were first identified, then analysed and finally evaluated before treatment. In this paper, the identification was done using eight semi-structured 1–2 hour long interviews. A Bayesian network (BN) was created to carry out the analysis part. Finally, the results were analysed using the mine's current risk evaluation method. Use of BN, for both forward inference to carry out risk assessment and backward inference to update prior probabilities and to facilitate incident investigation, were also demonstrated.

There are several methods to carry out risk assessment for stope collapse incident in an underground mine. Risk management best practices are directed by the International Organization for Standardization (ISO) 31000:2009 (ISO 2009). ISO 31000:2009 sees risk management as a process consisting of risk assessment and risk treatment, carried out in a specific context and supported by communication and consulting. The process is continually monitored, reviewed and developed as a typical 'plan-do-check-act' cycle. The risk assessment part of the process consists of identifying the relevant risks and hazards (risk identification), analysing the likelihood and impact of risk events to establish a total risk level (risk analysis), and evaluating the effects to the organisation of such a risk realising and whether or not such a risk is tolerable (risk evaluation) (ISO 2009).

Methods utilised in this study included semi-structured theme interviews and a BN analysis. First, interviews were used to establish the working context (the mine, company etc.). Risk identification used the interviews as input as well as repeating themes found in the responses of interviewees. Risk analysis was carried out using BN analysis for estimating the likelihood of events, while the interviews were used to establish the impacts of the events. Finally, risk evaluation was partially based on the interview responses. The risk management process with inputs is visualised in Figure 1.

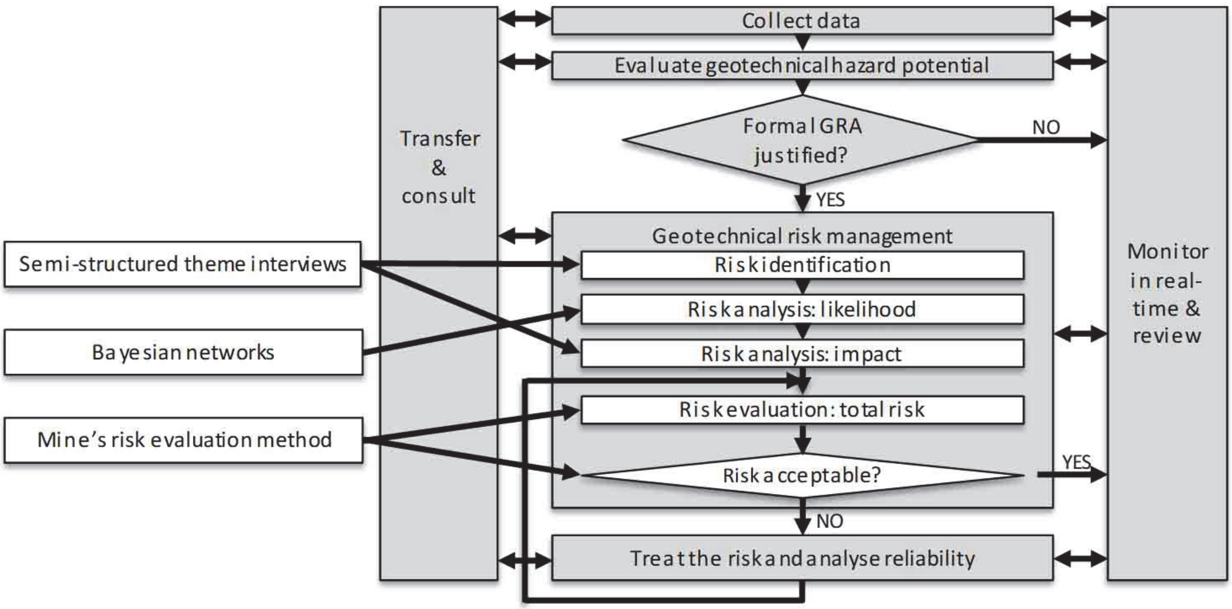

Figure 1 Inputs for the risk management process (modified after Mishra et al. 2017)

2 Risk identification

For risk identification, a set of semi-structured theme interviews were carried out at the target mine between 4 and 8 September 2017. The focus groups were selected to represent a wide range of mine personnel from various disciplines. A total of eight interview sessions were carried out over the course of one work week. The interviews ranged in length from approximately 1 to 2 hours. All interviews were recorded and later transcribed. The focus groups and interview dates and times were as follows:

1. Chief rock engineer (4 September 2017, 8:00 am).
2. Mine planning (4 September 2017, 11:00 am).
3. Blasting (5 September 2017, 9:30 am).
4. Geologists and the head geologist (5 September 2017, 11:30 am).
5. Operations manager (7 September 2017, 11:30 am).
6. Mine design 1 (7 September 2017, 1:00 pm).
7. Head of underground mining operations (7 September 2017, 2:00 pm).
8. Mine design 2 (8 September 2017, 8:30 am).

The interviews were conducted so that a set of standardised questions were asked, after which follow-up questions were freely asked. The standardised questions asked were the following:

1. What kind of geotechnical hazards are present in the mine?
   a. How severe are those hazards? How is the level of severity decided?
   b. What is their frequency?
   c. What are the observed causes for those hazards?
   d. How do you react to those hazards?
2. How do you assess rock mass competency? Why this method?
3. How is ground support designed?
4. What methods are used to assess the overall stability of mining area?
5. Do you perform any periodic measurements? What and how often?
6. Do you perform any real-time monitoring? What?
7. How do you perform geotechnical risk assessment?

In addition to the interviews, a questionnaire form with more detailed questions was delivered to key personnel. This questionnaire included basic information on the mine such as rock type, main rock formation, and depth, and technical details on things such as:

1. Mining method.
2. Ground support type and effectiveness.
3. Data collection, recording and storage.
4. Risk management and responsibilities.
5. Communication and data management.

Results of the interviews are summarised below showing what was identified as a potential contributor to stope collapse, what was being used to measure the presence and impact of the contributor and what was being done to mitigate it. It was noted that the mine was experiencing between four to six large collapses per year, with partial collapses being more common with up to 10–12 affected stopes per month. Some mine personnel believed that 30–50% of all stopes in the mine were experiencing some form of collapse. In this study, partial collapse is referred to when the volume of the excavated stope is more than planned, such as in the case of overbreak and sloughing. Large or full stope collapse is referred to in instances where the collapse extends beyond the roof of the stope. The reason behind the difference in the opinion, and at times the causes behind the incidents, were due to the way incidents were recorded at the mine. The highest priority for investigation was given to incidents where ore loss occurred and the agenda behind the investigation was largely focused on the cause. High level investigations were carried out and documented for full collapses, while partial collapses were not investigated. The investigation was described as varying in quality and contained a written description of the event and sometimes speculation into the cause and detailed location.

The causes identified through the expert interviews were grouped into evaluation categories to be later used in the BN driven risk assessment:

1. Presence of geological structure(s)

   Presence of geological structure(s) such as intersecting faults or fractures was unanimously considered to be the top cause behind stope collapse. Apart from the mere presence of a discontinuity, the presence and quality of filling material was identified as a contributor to the stope collapse. It was noted that while dense geological mapping made sure that no large features were missed along the mapping line, the orientation of the dominant joint set could still lead to some features being missed.

2. Rock strength

   Brittle ore was known to be prone to collapse. These rocks often resulted in competent geological strength index (GSI) values (Hoek 1994; Marinos et al. 2005) but were known to be mineralogically weak.

3. Stress field

   Stress estimation was carried out as part of the stope design as stress was considered as one of the contributors towards collapse. It was noted that the stress field got complicated as the stope approached closer to the former open pit in the mine increasing the risk of collapse.

4. Groundwater

   Increase in observed water was identified as one of the potential contributors to the collapse especially when the stope was known to have chalk fillings in discontinuities which reacted with water. Groundwater was not considered as a frequent cause to stope collapse in the mine.

5. Transition zones

   Stopes containing transition zones, where the ore came in contact with the waste rock, were identified as a problem area and likely to experience collapse.

6. Mining sequence

   Secondary stopes were noted to be more likely to collapse than primary stopes by some responders. Others felt that quality of reinforcement and consolidation was good enough for the phase to not have an impact on the collapse. Error in mining sequence was identified as a potential cause.

7. Open time and span of excavation

   Long and wide stopes were expectedly reported to be more prone to collapse compared to short and narrow stopes. The same applied to stopes which had been open for a long time. 'Long' was used as a subjective term and no trigger time was reported beyond which a certain stope become more prone to collapse.

8. Blasting

   Blasting activity was reported to be one of the identified causes in some of the collapse. Between firing sequence and charge density, improper charge density was reported to be more likely of a cause than poor blasting.

9. Neighbouring stope quality

   The success or failure of adjacent stopes was often used as a precursor of the current stope success.

10. Ground movement

    Ground movement was considered as a good indicator of potential collapse.

3 Current risk management methodology at the mine

Current risk management at the mine followed the broad principle outlined in Figure 2. Preliminary risk assessment was carried out using guidelines from a 'fact sheet'. These sheets carry subjective lessons learned from previous incidents and experiences. Current best knowledge for the planned excavation is evaluated in terms of GSI value, known geological structures from cores, interpreted geological structures from neighbouring stopes, collapse history of neighbouring stope etc. These observations are subjected to an expert assessment by the rock engineer, who then assigns a risk score from 1 to 3, with 3 being the worst.

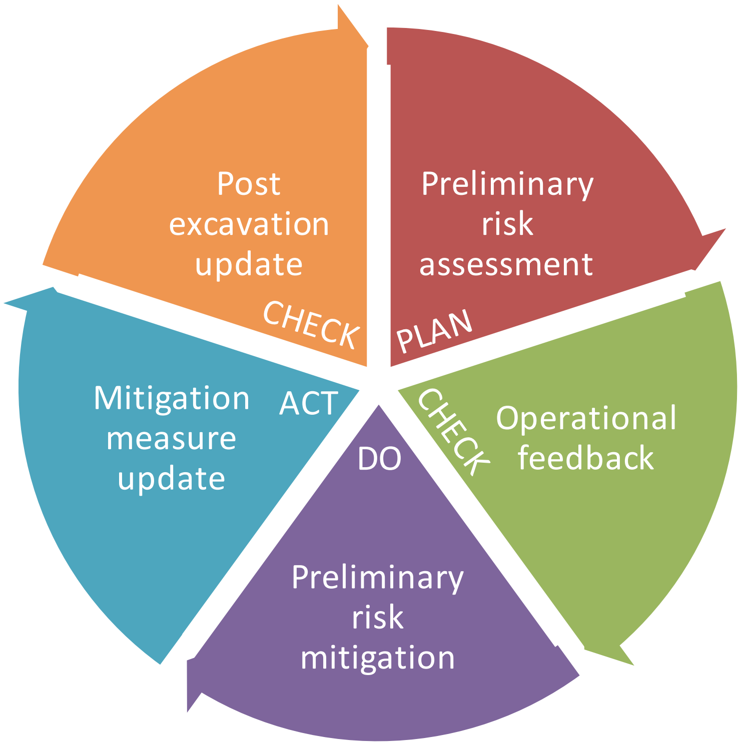

Figure 2 Current risk management process at the mine

Currently, the process is subjective to the engineer's expert opinion and does not use absolute limits for risk classification. If the risk is assigned a score of 3, the excavation plan is altered to manage the risk. General mitigation is done by reducing stope width, changing the direction of excavation and by reducing the open length of the stope. Based on the risk identified, suitable reinforcement changes are planned for the excavation. The mine currently has nine standard reinforcement plans for different locations and rock types with specific reinforcement plans for weak rock, standard ore, brittle ore, serpentinite-based ore, etc. Cable bolting is considered on a case-by-case basis.

Operational feedback from drilling crew and operational crew is taken into account when planning additional measures. The drilling crew provides input on the preliminary quality of rock and any observed discontinuities. Although part of the process, the rock engineer considered that operational feedback could be obtained and recorded in a better format. This feedback is used to revise the mitigation measures, if necessary. Any collapse during the stoping process is recorded in the excavation log. Once the stoping is completed, the stope is scanned and any collapses are recorded into the excavation log. If a full collapse happens during the process, a detailed investigation is carried out. Any relevant observation during and post-excavation affecting geotechnical risk are added to the fact sheet to be used in the preliminary assessment of the next stope.

Interviews with the chief rock engineer indicated that the current risk classification was adding value to the business in assessing and identifying the risk in advance. However, it was also brought to attention that the risk classification could be improved through improved event history tracking, better operational feedback and logging of feedback. The next section describes how existing risk management practice could be adapted using BNs to forecast risk, revise estimates using feedback and carry out incident investigation of partial and full stope collapse.

4 Risk analysis using Bayesian networks

BNs use Bayes' theorem (Bayes & Price 1763) to define conditional relationship between two or more variables. It can be used to represent the conditional relationship between a hypothesis and evidence as shown in Equation 1:

$$P(H_i|E) = \frac{P(E|H_i) \times P(H_i)}{P(E)} \tag{1}$$

where:

$P(H_i|E)$ = probability of a hypothesis (H_i) being true given the evidence (E).

$P(E|H_i)$ = likelihood of observing the evidence (E) if the hypothesis were true.

$P(H_i)$ = prior probability of the hypothesis.

$P(E)$ = probability of observing the evidence.

Bayes' equation with hypothesis and evidence can be used in the rock mechanics context to calculate probability of an event. For instance, based on the interviews at the mine one of the hypotheses is that brittle rock contributes to stope collapse. The Bayes' theorem version of this is shown in Equation 2:

$$P(Brittle\ ore_i|Stope\ collapse) = \frac{P(Stope\ collapse|Brittle\ ore_i) \times P(Brittle\ ore_i)}{P(Stope\ collapse)} \tag{2}$$

where:

$P(Stope\ collapse|Brittle\ ore_i)$ = likelihood (represents the percentage of stope collapses that happened in brittle ore in the past and can be obtained from historical evidence).

$P(Brittle\ ore_i)$ = prevalence of brittle ore in the mine (geological mapping can provide this information).

$P(Stope\ collapse)$ = current failure rate of stopes in the mine.

i = various states of the hypothesis.

For instance, the presence of brittle ore can either be Boolean with two states such as 'yes' or 'no', or the brittleness magnitude can be more descriptive with multiple states such as high, moderate, low, etc. Equation 2 is solved for all states of the hypothesis to arrive at the probability.

Figure 3 shows the basic structure of a BN which has been modified from the work done by Smith (2006), and how it can be used for decision-making. H_1 and H_2 nodes represent the various hypotheses, which are associated with evidence. In the stope collapse example, the various hypotheses can be two of the ten different reasons identified to be related to stope collapse in the mine. Node E represents stope collapse. The arrows mean that E is conditional or dependent on H_1 and H_2. The prior belief represents our current best understanding of how prevalent the hypothesis is. The nodes from which an arrow originates are called parent nodes while the nodes at the end of the arrows are called child nodes. The cause effect relationship is defined using historical data, if available, using conditional probability tables (CPT). In the absence of historical data, expert opinion can be used to create the BN, which can be then used to calculate subjective posterior probabilities.

Once the BN is constructed and solved with prior probabilities, it gives the probability of stope collapse *P(E)*. This process of solving for the probability of evidence is called forward inference. However, once a stope collapse happens, the BN can also be solved in reverse using Equation 1 to arrive at the probability of various hypotheses (geological structure, blasting, etc.) that could have caused the stope collapse. This process of solving for the hypothesis probability is called backward inference. The nodes and the arrows form the causal model as they define causation for an event *E*. BN is the process of use of CPTs to carry out inference.

The process of updating the network with observed data to recalculate prior probabilities is referred to as the decision-making model. For instance, a BN can be constructed to forecast stope collapse risk and the same BN can be solved in reverse to evaluate the most likely cause behind a stope collapse that has already occurred. Likelihood evaluation based on Bayesian networks can therefore be used to carry out both risk assessment for an event that has not happened and incident investigation for an event that has happened.

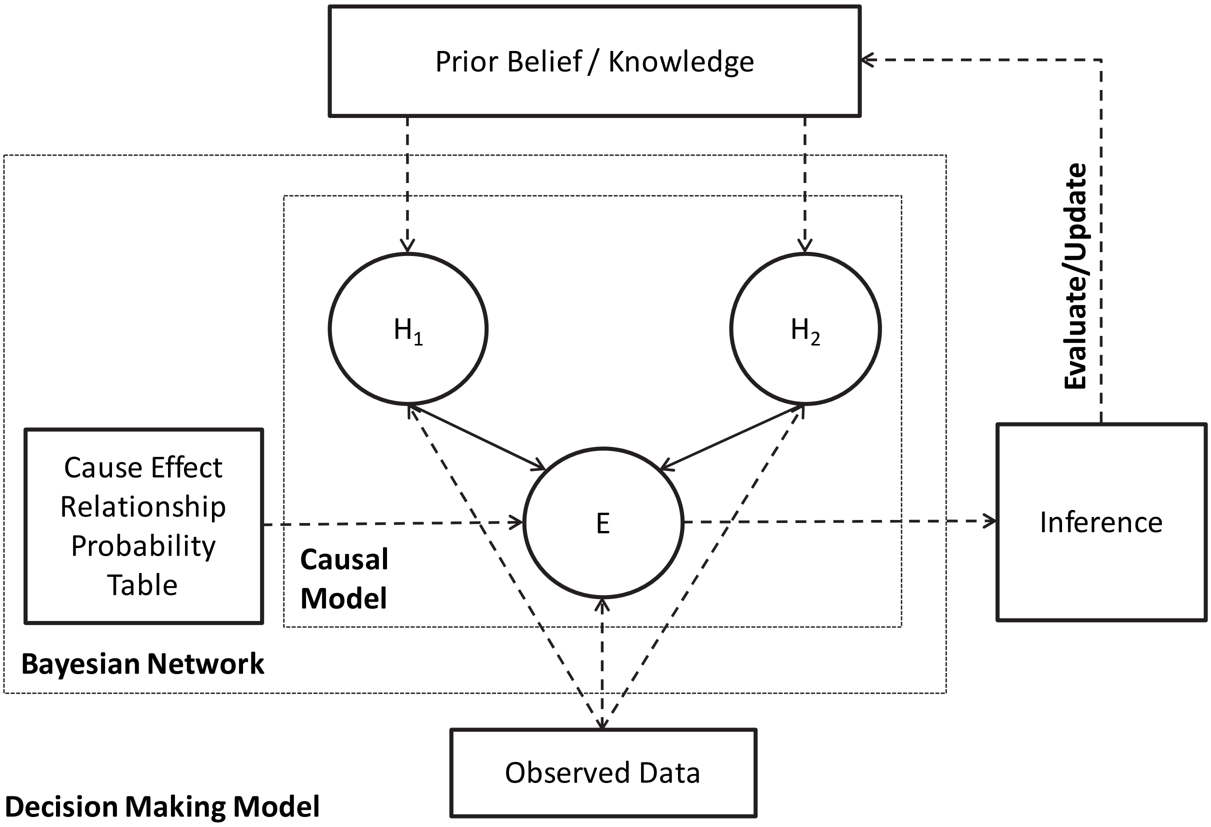

Figure 3 Basic structure of a Bayesian network and how it can be used for decision-making (after Smith 2006)

The ten contributors to stope collapse at the mine were grouped into three subcategories for the purpose of risk management. In order to limit the scope of the paper, the contributors were only evaluated for their likelihood, while consequence assessment of the stope collapse was left out. The purpose behind is two-fold. First, to categorise them into similar nodes. Secondly, to not have more than three parent nodes to a child node as this helps reduce the complexity of the CPTs for child nodes (Fenton & Neil 2012). The first such category was 'rock mass characteristics', which covered the causes arising from the properties of the rock. Geological structure, rock mass strength, groundwater and transition zones were classified under rock mass characteristics. Mining sequence, blasting, excavation span and time, and stress field were classified under the subcategory 'mining-induced characteristics'. Ground movement and neighbouring stope quality were classified under 'failure symptoms' as they do not cause the failure but are a sign that a failure is likely. Every subcategory was solved using individual BNs to create risk score per subcategory.

The subcategories were then combined to give the final probability of stope collapse. Each of the nodes in the BNs was assigned the Boolean nodes of 'yes' and 'no". 'Yes' indicated that a node would contribute to the stope collapse while 'no' meant that the node would not contribute to stope collapse. While Boolean nodes help simplify the BN, they present the challenge of having to define finite hard bounds for a parameter that is continuous in nature, such as stress and deformation measurement, joint set numbers etc. This problem can be tackled by entering percentage probability values as 'soft' evidence instead of the binary 'yes' or 'no'. For instance, instead of assigning a 'yes' value to the parameter 'geologic structure', a probability of 70% can be assigned to 'yes' implying that there is a 70% chance that the geologic structure will contribute to collapse in a particular stope.

Once the appropriate parent and child nodes were decided, the BN for stope collapse was constructed as shown in Figure 4 which is discussed later in the paper. Each parent node was then assigned a prior probability. Due to lack of historical data, the prior probabilities in this example have been assumed for representation purposes. The child nodes were then assigned conditional probability values based on their relationship with the parent node. These values were assumed as well. Table 1 shows the CPT for all the child nodes used in the BN. The Boolean values 'yes' and 'no' for the column 'Node states' represent the states of the parent nodes while the Boolean values for the column 'Node' represent the state of the parent node. For instance, the first probability entry of 80% represents that when parent node 'geologic structure' value is 'yes' and parent node 'groundwater' value is 'yes', the probability of the combined child node "groundwater and geology" contributing to stope collapse is 80%.

Table 1 Conditional probability table (CPT) for all the child nodes used in the Bayesian network

CPT for node	Node	Node states							
Groundwater and geology	Geologic structure	Yes				No			
	Groundwater	Yes		No		Yes		No	
	Yes	80%		60%		20%		5%	
	No	20%		40%		80%		95%	
Rock mass characteristic	Groundwater and geology	Yes				No			
	Rock strength	Yes		No		Yes		No	
	Transition zone	Yes	No	Yes	No	Yes	No	Yes	No
	Yes	95%	80%	80%	70%	80%	60%	70%	5%
	No	5%	20%	20%	30%	20%	40%	30%	95%
Span and stress	Excavation span and time	Yes				No			
	Stress field	Yes		No		Yes		No	
	Yes	95%		70%		70%		5%	
	No	5%		30%		30%		95%	
Mining-induced	Span and stress	Yes				No			
	Blasting	Yes		No		Yes		No	
	Mining sequence	Yes	No	Yes	No	Yes	No	Yes	No
	Yes	95%	90%	80%	60%	70%	70%	80%	5%
	No	5%	10%	20%	40%	30%	30%	20%	95%
Failure symptom	Ground movement	Yes				No			
	Neighbouring stope	Yes		No		Yes		No	
	Yes	99%		90%		80%		1%	
	No	1%		10%		20%		99%	

The probability values used in the CPT were assumed with subjective guidance from the interview process. For example, the experts were unanimously of the opinion that the presence of geologic structure often contributed to stope collapse while presence of groundwater was not a common cause for stope collapse. Therefore, the probability of the combined child node 'groundwater and geology' was assigned a value of 60% when the child node 'geologic structure' had the state 'yes' and 'groundwater' had the state no. The probability value was however dropped to 20% when the node states were reversed for 'geologic structure' and 'groundwater' emphasising the relatively higher influence of geological structures on stope collapse as compared to presence of groundwater. The probability of stope collapse was defined using a 'NoisyOr' function (Fenton & Neil 2012) as shown in Equation 3:

$$P(Stope\ collapse) = NoisyOr\begin{pmatrix} Rock\ mass & 25\% \\ Mining\ induced & 25\% \\ Failure\ symptom & 40\% \\ Leak & 10\% \end{pmatrix} \tag{3}$$

The NoisyOr function assigns the percentage contribution that each of the subcategory will have on the stope collapse. For instance, 'rock mass, 25%' indicates that rock mass characteristics have a 25% weight in deciding the stope collapse. The 'leak' value of 10% represents the probability of stope collapse even when all the other nodes in the BN have a favourable value. Leak represents the possibility of not having accounted for all the influencing values in a stope collapse.

The probability values shown for the parent nodes are the assumed priors. The probability values for the parent nodes were obtained by solving the CPT values for the parent node through the process of marginalisation (Spiegelhalter & Lauritzen 1990). As shown in Figure 4, the baseline likelihood of stope collapse with the assumed data is estimated at 37%. This model can now be used to carry out stope collapse likelihood estimation for any stope in the mine. In order to carry stope specific risk assessment, all available information is entered as evidence in the BN. For instance, if it is found that that adjacent stopes had a collapse, the probability for neighbour stope can be changed from 5 to 100% For a parameter where the information for the specific stope is unknown, the site average (used as priors in the nodes) can be left unchanged. The model can now be re-run to calculate the collapse probability for the specific stope.

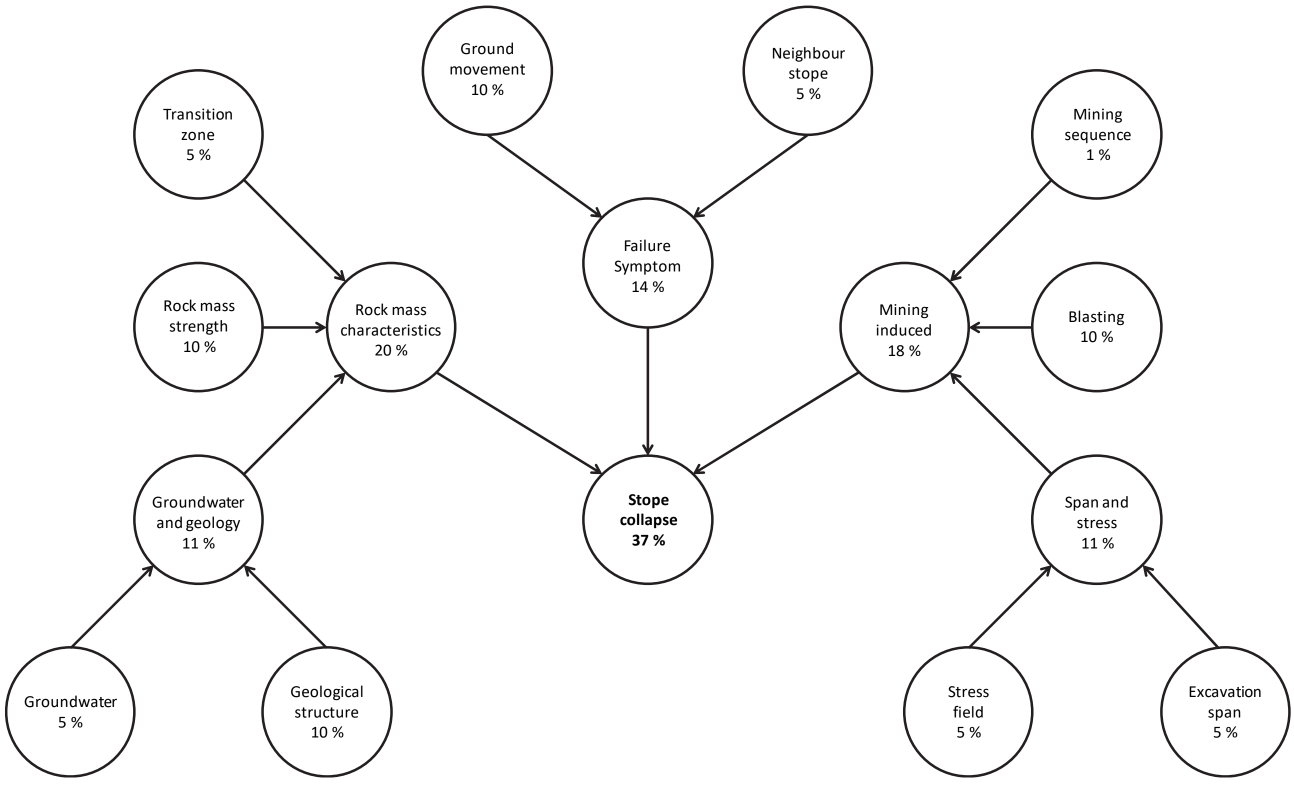

Figure 4 Bayesian network for stope collapse

5 Combining real-time instrumentation with observation-based BN

One of the disadvantages of the BN showed in Figure 4 is that the accuracy of the BN in its current form can only be improved with every subsequent stope collapse. When a stope collapse is observed, it can be entered as evidence by entering its probability at 100%. Running the model with this evidence recalculates the availability of all the other nodes indicating the likely cause of collapse using backward inference. As information about other nodes becomes available through incident investigation, their values can be entered as evidence to narrow down the likely causes. While this is a useful tool in carrying out incident investigation and revising the BN to include relevant nodes, the collapse can be severe enough to cause large financial losses to the business before the BN achieves the required accuracy. One of the ways to calibrate the model is to carry out numerical modelling to determine thresholds at which the stope would collapse. Numerical modelling, however, requires competent resources and sufficient geotechnical information to accurately model the stope collapse which may not always be readily available or could be prone to modelling error. This problem can be further tackled by instrumenting certain stopes and incorporating the instrumentation data into the BN. For instance, extensometers can be installed on a few selected stopes with the capability of real-time data transfer. Real-time feedback from extensometer can be used to replace the ground movement node for the stopes where the instrumentation has been carried out. Feedback from the real-time instrumentation can then be used to assign evidence to the stope collapse node. For example, if the ground movement feedback from the extensometers exceeds a certain threshold, stope collapse can be assigned a probability of 100%, assuming that at the current rate of ground movement and without any intervention, stope collapse is certain. These thresholds can be created either through expert opinion or can be obtained by carrying out a controlled collapse in a mined out stope. Alternatively, results from numerical modelling can help set up deformation thresholds beyond which a stope collapse is imminent. Solving the BN now revises the prior probability of all nodes to indicate which of the identified caused are most likely the reason behind the ground movement. If none of the nodes in the BN explain the ground movement, additional investigation should be carried out to identify factors contributing to ground movement and stope collapse.

The updating of stope collapse evidence on the basis of real-time instrumentation feedback doesn’t need to be binary in form of either 0% or 100%. A ‘soft’ evidence as discussed in section 4 can be used to assign non binary evidence. An example of the relationship between the real-time node and stope collapse node’s soft evidence is defined using assumed data in Table 2.

Table 2 Soft evidence criteria for stope collapse based on ground movement data

Real-time ground movement data (mm/day)	Probability of stope collapse (%)
1 to 3	60
4 to 10	80
>10	95

Figure 5 shows the modified BN from Figure 4 with real-time extensometer data node replacing the ground movement node. Evidence is received from the real-time extensometer data in the form of 7 mm per day. This information is then used to update the soft evidence for the stope collapse node. Solving the BN with the soft evidence using backward inference recalculates the prior probabilities for all the nodes in the BN. This shows the recalculated probability of each node being a contributing factor towards the potential stope collapse. These nodes can now be verified through site investigations to either conclude on the contributing node or point at missing information if none of the nodes explain the potential failure.

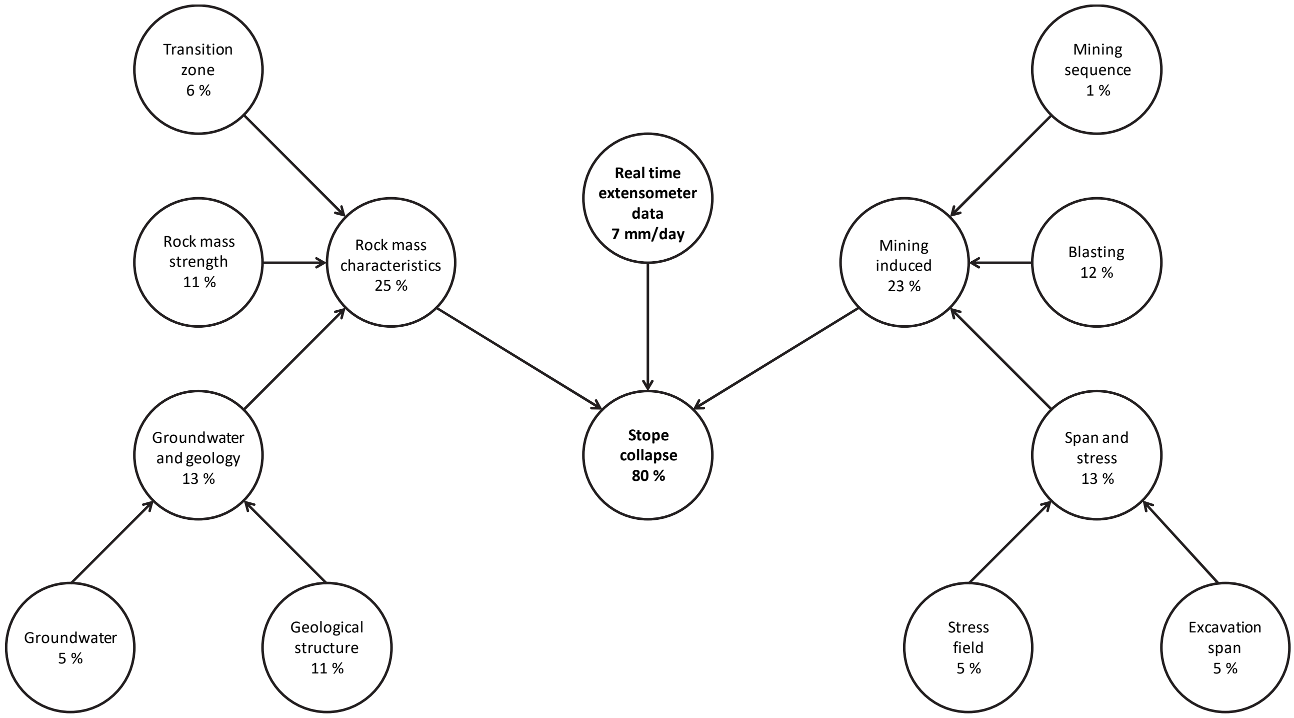

Figure 5 Stope collapse Bayesian network example solved using real-time data and soft evidence using backward inference

6 Discussion

BNs enable the use of expert opinion to kick start the risk assessment process. The existing risk methodology at the mine depended on the subjective opinion of the rock engineer. Lack of detailed investigation reports on stope collapse incidents made it difficult to understand if the possibility and degree of collapse were predicted in the informal risk assessment. BN-based risk assessment can help in giving a formalised structure to the subjective risk assessment process. This improves the repeatability of the stope collapse risk assessment when carried out by a different expert. The possibility of backward inference to carry out incident investigation using BN enables validation of expert opinion in stope collapse assessment. This not only enables updating of the prior probabilities based on incident data, it also points at possible causes to stope collapse which may not have been modelled if none of the nodes can explain the incident. The ability to work with expert opinion in the absence of historical incident frequency and also gives BN-based risk assessment the advantage of easier adoption in a mine site as a form of formal risk assessment. The ability to update prior probabilities also encourages mine sites for improved data collection and incident investigation.

While the use of subjective priors in absence of historical data is beneficial to start the risk assessment process, it is also one of the main disadvantages of BN-based risk assessment. If the prior probability values used in the model vary significantly from actual values, it can take a number of stope collapse incident investigation to correct the prior and conditional probabilities. Additionally, the lack of expert knowledge or incorrect causal models used in stope collapse prediction will produce inaccurate forecasts. The proposed methodology only discusses the likelihood assessment of whether the stope collapse will happen or not. A complete risk evaluation needs to consider consequence assessment of the stope collapse. The BN can be expanded to include the various possibilities of consequence such as ore loss, production stoppage, injury and/or fatality etc. While the prior probabilities affecting the likelihood can be obtained using numerical modelling in absence of actual incident, prior probabilities for factors affecting consequence are difficult to model and are highly subjective in nature. An example guideline for estimating the total cost of accidents in mines is given by Blumenstein et al. (2011).

Once the risk has been identified and quantified, the next key step is to mitigate the risk if it exceeds the tolerable level at the mine. Once a tolerable level of risk is determined, the network can be solved to carry out backward inference and assign acceptable probabilities to each contributing node. Periodic inspections can then be carried out to see if the nodes are meeting the acceptable probability targets. BN-driven risk assessment also enables the identification of the most likely causes behind an incident. Risk mitigation measures can be aimed at reducing nodes with the highest contribution to stope collapse. Once the mitigation measures are put in place, real-time feedback from instrumentation can be used to measure the effectiveness.

7 Conclusion

For risk identification, eight semi-structured theme interviews were carried out at a Finnish metal mine. Ten causes for stope collapses could be identified. A BN was constructed based on the identified causes to calculate stope collapse likelihood. Due to lack of historical data, prior probabilities were assumed. Using these assumptions, the stope collapse likelihood was 37%. As historical data is not always available, an example was presented on how to use real-time data in conjunction with the BN presented. This example uses the ground movement velocities along with a soft evidence criterion to replace the need for ground movement historical observations. The proposed methodology can now be tested in the mine to validate the accuracy of the expert opinion behind stope collapse causes. Final risk is a result of multiplication of likelihood and consequences. The risk can be used in the design for risk treatment actions.

Acknowledgement

The authors gratefully acknowledge the financial support provided by the ORMID research project funded by the Academy of Finland under the grant no. 297770.

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